Patterns and drivers of wildfire occurrence and post-fire vegetation resilience across scales in Portugal

João Paulo Couto Sá Torres

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Orientador
João Pradinho Honrado, Professor Auxiliar, Faculdade de Ciências da Universidade do Porto

Coorientador
Maria José Perestrelo de Vasconcelos, Investigadora Auxiliar com Agregação, Instituto de Investigação Científica Tropical

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Abstract

Wildfire occurrence and post-fire ecosystem resilience are complex phenomena, driven by a multitude of factors at several spatial and temporal scales. These drivers include environmental conditions, human factors, landscape and ecosystem traits, and attributes of fire events and fire history. This dissertation addresses the complex patterns of wildfire occurrence and post-fire regeneration across scales in continental Portugal, a small but heterogeneous country holding the highest records of wildfire occurrence in Europe. Results of four studies are presented, of which two address national to (sub-)regional wildfire patterns and drivers, and two provide analyses of regional and local patterns and drivers of post-fire resilience. These four studies are based on several types of data and modelling techniques, and together they are intended to contribute to the understanding of wildfire occurrence and post-fire resilience as two key components of multi-scale fire risk management.

The first study analyses recent patterns of wildfires in continental Portugal and tries to identify its main drivers using machine learning techniques. The heterogeneity of environmental and socioeconomic conditions was found to be clearly reflected in the patterns of fire occurrence, and distinct groups of factors were shown to differentially influence fire occurrence in different regions across the country. The second study applied inductive logical programming to derive a set of rules to explain and predict the general patterns of wildfires in the Alto Minho sub-region, northwest of Portugal, and again the results highlighted the importance of considering internal heterogeneity of conditions (with an emphasis for landscape features) to explain and predict fire occurrence in small but complex regions. The third study provides evidence of the potential of remote sensing data and tools to assess changes in ecosystems driven by fire events as well as to analyse their post-fire recovery, particularly for functional state indicators. Finally, the fourth study uses vegetation and plant community data collected during in-field campaigns to assess the relative importance of geological factors and fire history as local controls of post-fire resilience.

The following main conclusions were drawn on the patterns of wildfire occurrence in heterogeneous countries and regions: (i) the ranking of fire factors or correlates can be revealed by analyses of historical fire records and tends to be region-specific in heterogeneous countries; (ii) the diversity of fire factors required to adequately explain and predict fire regimes is higher in the more heavily burnt regions; and (iii) machine learning modelling techniques are useful to explain and predict the patterns and drivers of fire occurrence in heterogeneous countries and regions. From the two studies of post-fire regeneration we concluded that: (i) using functional indicators of post-fire recovery allows capturing dimensions of resilience that are driven by distinct sets of factors; (ii) regional patterns of post-fire recovery rates are largely determined by size and other features of fire events, as well as by structural and functional attributes of pre-fire landscapes; and (iii) geology is an important factor or correlate of post-fire ecosystem resilience at regional and local scales.

Several lessons have been drawn for governance and management of fire risk across scales. First, regional to local rates and pathways of post-fire vegetation resilience are influenced by many distinct factors related to environmental conditions as well as to structural and functional features of landscapes and plant communities, and this should be taken into account for technical decision on active restoration of burnt areas. Also, fire recurrence and differential post-fire regeneration across burnt landscapes originate complex patterns of fuel biomass accumulation and connectivity, and this will influence the occurrence and spread of future fires over the landscape. We conclude that robust predictive modelling frameworks, coupled with historical fire datasets and remote sensing tools, can be important assets in the management of fire risk at several scales as well as in the monitoring of the effects of wildfires and other disturbances on the key structural and functional attributes of landscapes and the ecosystems therein. Therefore, continued effort should be made to promote the application of results and lessons learnt in the improvement of fire risk management across spatial scales and levels of political and technical decision.

Keywords:

Fire ecology, Multi-scale assessments, Modelling, Portugal, Post-fire resilience, Remote sensing, Vegetation, Wildfire patterns and drivers

Resumo

A ocorrência de incêndios e a recuperação pós-fogo dos ecossistemas constituem fenómenos complexos, determinados por múltiplos factores em diversas escalas espaciais e temporais. Estes determinantes incluem as condições ambientais, factores humanos, atributos da paisagem e dos ecossistemas, e características dos incêndios e do regime de fogo. Esta dissertação aborda os padrões complexos de ocorrência de incêndios e da regeneração pós-fogo em diversas escalas em Portugal continental, um país pequeno mas heterogéneo que regista os valores mais elevados de ocorrência de incêndios na Europa. São apresentados resultados de quatro estudos, dois relativos aos padrões e determinantes da ocorrência de incêndios no país e nas suas (sub-)regiões, e dois que analisam os padrões e determinantes regionais e locais de resiliência pós-fogo. Estes quatro estudos baseiam-se em diversos tipos de dados e ferramentas de modelação, e pretendem contribuir para a compreensão da ocorrência de incêndios e da resiliência pós-fogo enquanto dois componentes centrais da gestão do risco de incêndios em diversas escalas.

O primeiro estudo analisa os padrões recentes dos incêndios em Portugal continental e tenta identificar os seus principais determinantes com recurso a algoritmos de aprendizagem automática. Verificou-se que a heterogeneidade de condições ambientais e socioeconómicas se reflete nos padrões de ocorrência de incêndios e que diversos grupos de factores influenciam de esses padrões de forma distinta nas diversas regiões. O segundo estudo aplica programação lógica indutiva para derivar um conjunto de regras para explicar e prever os padrões gerais de ocorrência de incêndios na sub-região do Alto Minho, noroeste de Portugal, e os resultados reforçam a importância de considerar a heterogeneidade interna de condições (principalmente no que se refere às características da paisagem) para explicar e prever os padrões dos incêndios em regiões pequenas mas complexas. O terceiro estudo explora e evidencia o potencial dos dados e ferramentas de detecção remota para avaliar alterações nos ecossistemas promovidas pelos incêndios e para analisar a sua recuperação pós-fogo, particularmente no que se refere a indicadores funcionais de estado. Finalmente, o quarto estudo analisa dados de campo relativos a vegetação e a comunidades vegetais para a avaliar a importância relativa de factores geológicos e do histórico de incêndios enquanto controlos locais da resiliência pós-fogo.

Foram extraídas as seguintes conclusões principais relativamente aos padrões de ocorrência de incêndios em países e regiões heterogéneos: (i) a importância relativa dos factores causais ou correlacionados com a ocorrência de incêndios pode ser revelada por análises de registos históricos de incêndios e tende a ser distinta entre regiões em países heterogéneos; (ii) a diversidade de factores necessária para explicar e prever os regimes de fogo é maior nas regiões mais afectadas pelos incêndios; e (iii) os algoritmos de aprendizagem automática são úteis para explicar e prever os padrões e os determinantes da ocorrência de incêndios em países e regiões heterogéneos. Os dois estudos relativos à regeneração pós-fogo permitiram concluir que: (i) a utilização de indicadores funcionais de recuperação pós-fogo permite analisar dimensões da resiliência que são condicionadas por conjuntos de factores distintos; (ii) os padrões regionais das taxas de recuperação pós-fogo são largamente determinados pelo tamanho e outras características dos incêndios, bem como por atributos estruturais e funcionais das paisagens pré-fogo; e (iii) a geologia é um importante factor causal ou correlacionado com a resiliência pós-fogo dos ecossistemas às escalas regional e local.

Os resultados obtidos permitem extrair um conjunto de implicações para a governança e a gestão do risco de incêndio em várias escalas. Em primeiro lugar, as taxas e os percursos de regeneração pós-fogo são influenciados por numerosos factores relacionados com as condições ambientais e com as características estruturais e funcionais das paisagens e das comunidades vegetais, e este facto deverá ser tido em conta na tomada de decisões técnicas relativas ao restauro ativo de áreas ardidas. Além disso, a recorrência de incêndios e a capacidade diferencial de regeneração pós-fogo em paisagens submetidas a incêndios origina padrões complexos de acumulação e conectividade de biomassa combustível, o que influenciará a ocorrência e a propagação de incêndios futuros na paisagem. Conclui-se que molduras robustas de modelação preditiva, combinadas com dados históricos de incêndios e ferramentas de detecção remota, constituem instrumentos importantes na gestão do risco de incêndio em várias escalas, bem como na monitorização dos efeitos do fogo e de outras perturbações nos principais atributos estruturais e funcionais das paisagens e dos ecossistemas nelas contidos. Assim, deverá ser continuado o investimento na aplicação prática de resultados e conclusões na melhoria da gestão do risco de incêndio nas diversas escalas espaciais e níveis de decisão política e técnica.

Palavras-chave:

Avaliações multi-escalares, Detecção Remota, Ecologia do fogo, Modelação, Padrões e determinantes dos incêndios, Portugal, Resiliência pós-fogo, Vegetação

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1. Introduction

1.1. Wildfires in the context of landscape change

1.1.1. Fire and the science of Fire Ecology

Fire is a frequent phenomenon in many ecosystems and landscapes around the world. It can be seen as an ecological disturbance (Turner, 2010), a land management mechanism (Moreira *et al.*, 2011) and/or an environmental hazard with important socioeconomic consequences (Román *et al.*, 2012). Throughout time wildfires have contributed to the shaping of ecosystems and landscapes, inducing plant and animal evolution (Pausas and Schwilk, 2012) as well as driving biotic community structure and dynamics (Pausas *et al.*, 2008). The emergence of humans as landscape managers changed the fire regime in many ecosystems, either by increasing its frequency (by the deliberate use of fire to change land cover) or by diminishing both its frequency and severity (e.g. by contributing to fragmentation of the landscape and through the limitation of ignitions in certain areas; Keane *et al.*, 2004).

With the growth of the available methods and technologies as well as of the number of researchers investigating it and of the resources allocated for it, a branch of ecological sciences ("Fire Ecology") has emerged as the study of the relations between wildfires, organisms, ecosystems and society (Bowman and Franklin, 2005). Fire Ecology is concerned with the processes linking the natural incidence of fire in an ecosystem and its ecological effects. It can be considered a sub-discipline of Landscape Ecology, since both span the temporal, spatial and social dimensions of landscapes (Whelan, 1995).

There are many terms around wildfire studies, with variations among world regions, countries and even authors. In the scope of this thesis, the term *wildfires* refers to fires of natural or anthropic origin, which occur in terrestrial ecosystems and propagate by consuming biomass, namely vegetation (Moreira *et al.*, 2011). In Europe, the most common term used is *forest fires*, whereas in the United States of America it is *wildland fires* and in Australia *bushfires*. These and other terms, such as *vegetation fires* or *landscape fires*, are considered synonyms (Pausas, 2012).

Fire disturbance is an ecological process, which can be considered natural within the range of its historical records in a given ecosystem (Bond and Keeley, 2005). Outside this range it can endanger the stability of that same ecosystem, just like extreme flooding or overgrazing. In the same way that the existence of overgrazed areas does not necessarily mean that herbivory is an artificial and harmful process to biodiversity, the existence of areas with anthropically increased wildfire frequencies does not mean that wildfires are always "unnatural". Moreover, wildfires are not necessarily harmful to biodiversity by themselves, but certain wildfire regimes can be (Pausas, 2012). Understanding wildfire regimes, their causes and changes, is paramount to a sustainable management of ecosystems (McPherson and DeStefano, 2003).

Wildfires are the direct or indirect cause of much economic damage. As an example, wildfires in Portugal during year 2005 caused economic damage worth almost €800 million and caused 13 fatalities. During the summer of 2007, wildfires caused 64 casualties in Greece, and according to the Greek authorities the economic damage was estimated at €2–5 billion (Papachristou, 2007; Petsini Arlapanou and Petsini Arlapanou, 2007).

Despite the resources invested in fire prevention and suppression, the number of fires in recent decades has continued to increase in Europe (JRC, 2012; Figure 1.1). If fact, fire exclusion promotes the accumulation of biomass across the landscape, thereby increasing fuel load and fire risk, a phenomenon known as the “fire paradox” (Silva *et al.*, 2010). There is thus growing concern about the ecological and socio-economic impacts of wildfires, particularly under a climate change context that may imply a future increase in the frequency and/or severity of wildfires in European countries (Piñol *et al.*, 1998; Mouillot *et al.*, 2002; Pausas, 2004; Arianoutsou, 2007).

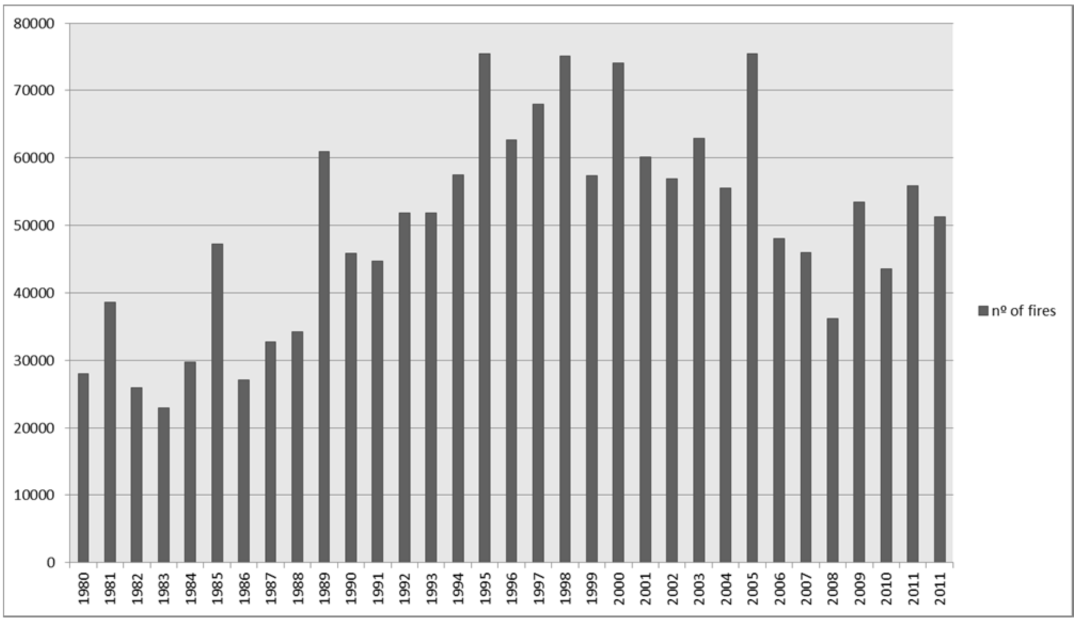


Figure 1.1. Joint number of fires in the five Southern Member States of the European Union (Portugal, Greece, Spain, France, and Italy) between years 1980 and 2012. Source: JRC (2012).

Studying and understanding ecological processes often requires a broad scope in time and in space. Therefore studying a single isolated wildfire does not enable managers or researchers to correctly understand the regional causes and/or consequences of wildfires. Instead, considering the fire regime is the usual process in wildfire research (Lloret *et al.*, 2003; Lawson *et al.*, 2010; Telesca, 2010).

A fire regime (FR) is the ensemble of characteristics of wildfires in a specific area or ecosystem throughout a large period of time, especially regarding their frequency, intensity, seasonality and type of propagation (Krebs *et al.*, 2010). ‘‘Fire regime’’ has become, in recent decades, a key concept in many scientific domains. In spite of its wide spread use, the concept still lacks a clear and widely established definition. Krebs *et al.* (2010) thoroughly reviewed the available bibliography and proposed a structuring of the most important categories (Figure 1.2). Some of the parameters belong to the core definition of FR (*sensu stricto*), describing when, where and which fires occur (see Figure 1.2- A). Nearly all the early definitions of fire regime corresponded to this strict sense (Gill 1975, 1977; Aldrich *et al.*, 1978; Christensen, 1985).

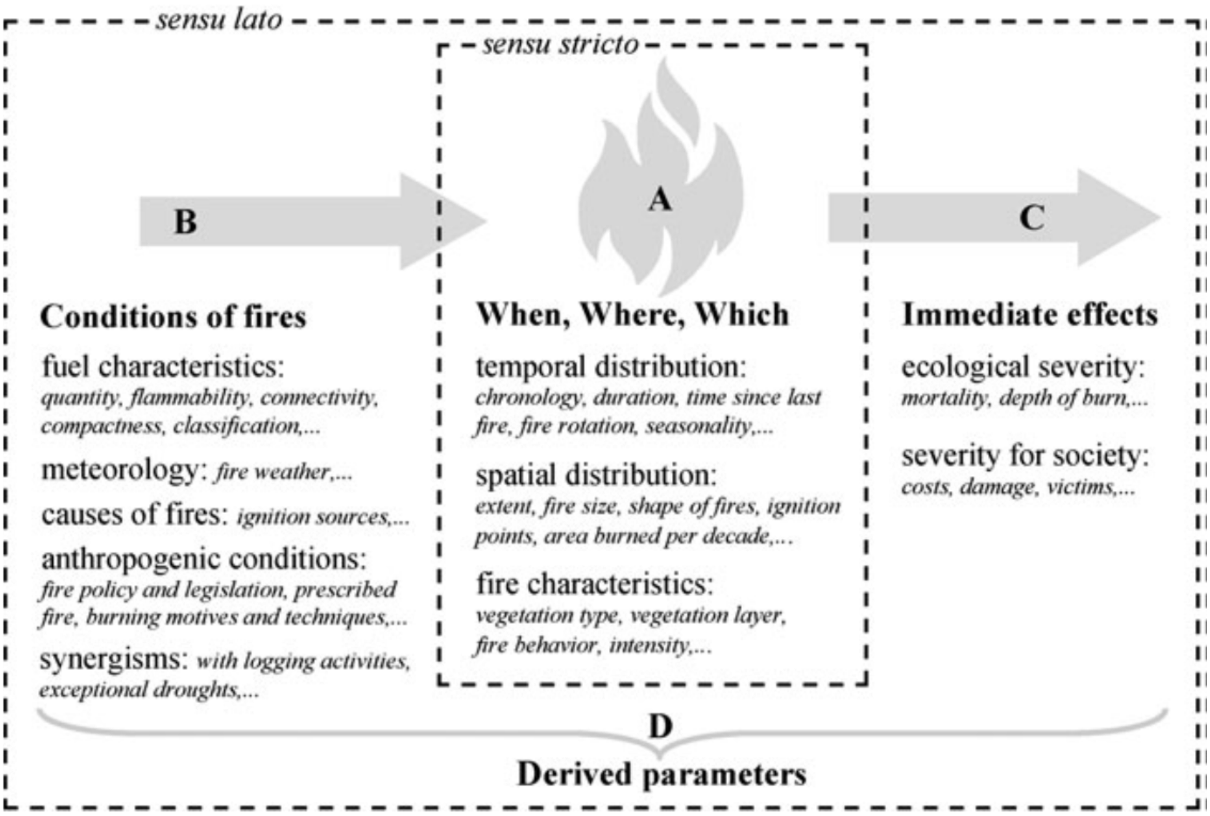


Figure 1.2 Representation of fire regime concepts. In the more exclusive definition (*sensu stricto*), a fire regime is a description by means of parameters of when, where and which fires occur (A); in a more inclusive definition (*sensu lato*), a fire regime may also include parameters that refer to the conditions of fire occurrence (B) and to the immediate effects of fires (C). Combining and analyzing the data of these three categories may result in further derived parameters (D). Source: Krebs *et al.* (2010).

A second category of parameters refers to the conditions of fire occurrence (see Fig. 1.2 - B), those are all the factors recognized as fire circumstances and prerequisites for fires (Booysen, 1984; Bond and Van Wilgen, 1996) that directly determine the timing, size, magnitude and characteristics of fire events. Finally, a third category of parameters that may be included in the broad definition of fire regime refers to the immediate effects of fires (direct impact of fires on ecosystems, human goods and infrastructures, see Figure 1.2- C).

Depending on the specific situation, parameters belonging to these categories can then be transformed and combined (see Figure 1.2- D). Derived and combined parameters have been more used in recent decades as increasingly complex instruments, methods and procedures for monitoring and modelling fire regimes have been developed. Examples of composite parameters include the analysis of burned areas according to fire severity classes (Morrison and Swanson, 1990, p. 19) or stand flammability related to the time since the last stand-replacing fire (Heinselman, 1981).

Even if fire regimes are very diverse (there are no two landscapes with the same regime), broad types of vegetation can be related with some features of fire regimes. For a wildfire to occur, there are three main conditions to fulfill: a source of ignition, plant biomass (fuel), and appropriated weather conditions (Pechony and Shindell, 2010; Pausas, 2012). As these conditions can often be met together, and in many different geographic contexts, wildfires may occur in almost every ecosystem around the world with very different regimes (Bond *et al.*, 2005; Whelan, 2005).

1.1.2. An overview of patterns and drivers of fire occurrence

In a permanently changing world, shifts in socio-economy, in land use and in the management of the territory, in human population densities and in climatic conditions affect and modify the regime of wildfires (Pezzatti *et al.*, 2011; Rogers *et al.*, 2011). These changes can (and often do) drive fire regimes outside their historical range, with severe consequences to ecosystems and to society. In ecosystems where wildfires were historically very rare, such as rain forests, the recent increase in fire frequency and size can be a real threat to biodiversity (Pueyo *et al.* 2010; Ciais *et al.* 2011). Even in more fire prone ecosystems, such as those of Mediterranean areas, the decrease of intervals between wildfires will also likely affect biodiversity if climate change predictions are confirmed (Pausas *et al.*, 2008; Moreira *et al.*, 2011).

The impact and importance of wildfires around the world make them crucial to understand regional and global ecological cycles. The regions where wildfires are more active are located in tropical and subtropical zones with high primary productivity and marked seasonality (Ciais *et al.*, 2011; Pausas, 2012). This is the case of the Savanna biome, where the high frequency of fire does not allow large amounts of biomass to be accumulated and so wildfires are usually of low intensity. In the other extreme are deserts and alpine regions, where the low productivity does not allow sufficient biomass to accumulate. Nevertheless, in some arid regions (e.g. central Australia) with enough herbaceous vegetation wildfires may play an important role in ecosystem dynamics. Mediterranean ecosystems represent an intermediate situation, where the natural wildfire return interval is situated in the dozen of years (Pausas, 2012).

Since wildfires are a common phenomenon to many types of ecosystems globally, the factors that determine them, as well as their regime, vary considerably (Pechony and Shindell, 2010). In productive ecosystems (temperate forests, rain forests, etc.), there is abundant biomass but the conditions for high flammability (e.g. low humidity) are rare. In these ecosystems fire regimes are determined by occasional dryness and are characterized by low fire frequency, but when, in exceptionally dry years, wildfires occur they are usually very intense and leave severe scars in the landscape (Tedim *et al.*, 2012). In dry regions, climatic conditions are usually optimal to fire occurrence, but the lack of biomass usually hampers fire propagation. These fire regimes are thus limited by fuel availability (Pausas and Fernández-Muñoz, 2011). In fact, as described above, the maximum fire frequencies occur in highly seasonal ecosystems, such as savannas, with a wet season that generates great volumes of biomass and a dry and hot season when this biomass is dry and is easily consumed by fire. In the Mediterranean, the maximum activity of wildfires occurs in dry scrubland, decreasing in moist ecosystems such as evergreen forests and even more in deciduous forests (Pausas, 2012; Azevedo *et al.*, 2013). The fact that relations between fire and climate are different in systems where fire is mediated either by dryness or by biomass implies that future climatic changes will affect fire regimes differently across regions (Pausas and Fernández-Muñoz, 2011).

Changes in social, economic and governance models frequently imply modifications in land use and landscape management (Pedroli *et al.*, 2006; Ribeiro and Lovett, 2009). Wildfire propagation is dependent of the spatial continuity and connectivity of the biomass fuel, therefore small changes in landscape structure can lead to abrupt changes in fire regime. In the Mediterranean region of Europe, industrialization and general social modernization produced drastic changes in many landscapes. Here, landscapes were traditionally submitted to a high agricultural and grazing pressure even in the highlands. Then, with generalized rural abandonment in the mid and late XX century, the amount and continuity of fuel biomass increased considerably and fire regimes changed accordingly (Moreira *et al.*, 2011; Pausas and Fernández-Muñoz, 2012).

Understanding the factors driving the spatial patterns of fire ignitions has important implications for vigilance, firefighting and prevention, public educational campaigns, and the implementation of legislation concerning human activities prone to cause wildfires (Montiel-Molina, 2012). Numerous studies have identified several factors influencing the spatial patterns of fire ignitions (Vasconcelos *et al.*, 2001; Mercer and Prestemon, 2005; Genton *et al.*, 2006; Nunes and Duarte, 2006; Catry *et al.*, 2007, 2009; Romero-Calcerrada *et al.*, 2008). Among these, variables related to human activities are rather important, particularly in southern Europe where the vast majority of wildfires have human origin (EC, 2008). For example, in Portugal and Spain about 97% of all successfully investigated wildfires were considered human-caused (DGRF, 2006; MMA, 2007). The coalescence of flammable vegetation and urban development and the high risk of ignition in peri-urban areas imply extreme threat to human life and property (Moreira *et al.*, 2011).

Wildfire regimes are rather variable according to spatial context, especially related to variations of climate and vegetation structure. The severity of the meteorological component of fire risk during the second half of the XX century suggests that climate change, rather than forest-related change, may well be the main driver behind fire regime modifications (Seidl *et al.*, 2011). However, evidence is mounting that the positive response of fire to more extreme weather and drought events is mediated by vegetation/fuel (Koutsias *et al.*, 2012; Pausas and Fernández-Muñoz, 2012; Pausas and Paula, 2012). In recent years, these factors jointly resulted in a brutal increase of the size and frequency of wildfires in most Mediterranean countries of Europe. This increase happened despite the parallel increases of the efforts to control an extinguish wildfires (Pereira, 2005).

1.2. Ecological changes induced by fire disturbance

Each type of ecosystem and landscape has a characteristic fire regime defined by the range of frequency, intensity, seasonality and type of wildfires (Krebs *et al.*, 2010). Recent changes in fire regimes have produced significant impacts on biodiversity and ecosystem functioning (Cochrane, 2003; Lavorel *et al.*, 2007). Consequently, there is increasing interest in disentangling the drivers of fire regimes world-wide (e.g. Westerling *et al.*, 2006; Marlon *et al.*, 2008; Krawchuk& Moritz, 2011) and in implementing this knowledge in predictive tools for environmental management (Lavorel *et al.*, 2007; Flannigan *et al.*, 2009).

Fire, ecosystems and landscapes share a long common history, with fire deeply influencing the condition and evolution of ecosystems and landscapes. With the frequent use by humans, fire has attained an unprecedented dimension of landscape transformation (Perry*et al.*, 2012). The impacts of fire on ecosystems are very diverse and dependent on a multiplicity of fire event and fire regime characteristics, some of the more important being the intensity of specific events, fire recurrence, and the type and pre-fire ecological condition of the ecosystem (Catry *et al.*, 2010). Fires can change environmental conditions, such as the composition and configuration of habitats, their resilience, their biodiversity, and even the processes of soil formation and loss (Certini, 2005; Bowman and Murphy, 2010). Depending on the size of the fire, the main effect on the landscape can be of homogenization (in the case of large sized fires), or of increases of spatial heterogeneity and fragmentation (in the case of small sized fires; Silva *et al.*, 2011). Moreover, wildfires may homogenize local landscapes while producing spatial heterogeneity at broader scales (Malkinson *et al.*, 2011). This can then yield rather contrasting (and scale-dependent) effects on future landscape flammability, biodiversity, ecological processes and ecosystem services (Proença *et al.*, 2010).

The impacts of wildfires on the ecology of ecosystems and landscapes can be categorized into: (1) direct effects on conditions and resources in burnt areas, (2) wider effects on landscape structure and functioning, and (3) direct and indirect effects on biodiversity. These broad types of impacts are briefly described in the following sections.

1.2.1. Direct effects on conditions and ecosystem functioning

By consuming vegetation, wildfires dramatically change several types of environmental conditions in the affected ecosystem, such as light availability, litter deposition, and microclimate (Chapin *et al.* 2011). The consumption of biomass releases large amounts of carbon from vegetation and soil into the atmosphere, eventually contributing to deterioration of air quality (Singh *et al.*, 2012). There are also emissions of other substances into the atmosphere, such as water, carbon monoxide, methane, nitric oxide and various volatile organic compounds (Pérez-Ramirez *et al.*, 2012).

Resource availability is also affected by fire in multiple ways, from soil degradation and decrease of organic matter to destruction of plant biomass for herbivores to feed upon (García-Corona *et al.*, 2004). Nonetheless, low intensity fires may contribute to rapid release of nutrients from organic matter, which allows a rapid colonization and biomass production by ruderal plant species (Grime, 2001). Open habitat specialists can also benefit from the occurrence of wildfires, and many predators will have increased opportunities for capturing prey (Letnic *et al.*, 2004).

Fires are known to alter soil properties that influence soil water retention and thereby hydrological regulation and the downstream provision of ecosystem services. They have been reported to decrease organic matter content (García-Corona *et al.*, 2004), increase bulk density (Ferreira *et al.*, 2009), change soil texture (Badía and Martí, 2003) and induce soil water repellency (DeBano, 2000). After fire, vegetation cover is totally or partially removed, which affects hydrological processes in the soil, increasing the general risk of floods and of erosion (Stoof *et al.*, 2012). Heating alters soil physical and chemical properties, which promotes surface runoff, inducing soil erosion and increaseing catchment-level sediment yield (Shakesby and Doerr, 2006). When those sediments reach the water lines, water quality is affected, as well as hydropower generation processes. Furthermore, the change of soil properties affects infiltration capacity and increases peak flows, affecting the timing of water flows and maximizing the risk of floods downstream. In addition, there is an increase of discharge, mainly because of surface runoff precipitation responses, which contributes to an increase of water quantity in the catchment, although quality may not be affected (Neary *et al.*, 2009).

Examples of other ecosystem functions and services negatively affected by wildfires include primary productivity and carbon sequestration (Huang *et al.*, 2009), timber and wood production by forests (Román *et al.*, 2012), and aesthetic value and recreation.

1.2.2. Wider effects on landscape structure and functioning

Disturbances play a fundamental role in shaping the structure and dynamics of landscapes (Turner and Dale, 1990), as landscape patterns are largely determined by the frequency, intensity, location and extension of disturbances (Pickett and White, 1985; Krumel *et al.*, 1987). At the same time the spatial propagation of disturbances across the landscape is a function of the abundance and arrangement of susceptible habitats (Turner *et al.*, 1989) and of their disturbance history.

Considering that fire is one of the main types of disturbances affecting Mediterranean landscapes, understanding how landscape structure affects the spatial spread of wildfires is a key issue for understanding their ecological implications and the role they play in landscape dynamics (Moreira *et al.*, 2009). As described above, fire disturbance can promote either landscape homogeneity or heterogeneity, depending on features of the fire event (e.g. spatial extent and intensity/severity; Vega-García and Chuvieco, 2006) and of the landscape itself (e.g. susceptibility of its habitat types to fire disturbance, spatial contrasts of flammability, and connectivity of the more susceptible habitat types; Zozaya *et al.*, 2011).

Changes in ecosystem and landscape functioning induced by fires have been mainly reported from studies based on satellite imagery and remote sensing methods. Those changes include drastic decreases of photosynthetic activity (e.g. Gouveia *et al.*, 2012) as well as shifts in vegetation phenology (e.g. Angelis *et al.*, 2012).

1.2.3. Direct and indirect effects on biodiversity

Wildfires are regarded as one of the main threats to Mediterranean biodiversity (WWF, 2003). Fire disturbance can have strong effects on the local patterns and dynamics of biodiversity (Pastro *et al.*, 2011). Such effects may be negative (direct or indirect) or positive. Among negative impacts, the most important direct effect is mortality, which affects particularly those organisms with limited mobility, such as plants and small non flying animals (Banks *et al.*, 2011, Pastro *et al.*, 2011). Indirect effects involve processes such as habitat degradation and changes in environmental conditions and resource availability (e.g. Martín-Martín *et al.*, 2013; see above), as well as landscape fragmentation, including habitat loss and increased isolation of remaining habitat patches (Lloret *et al.*, 2002). For example, in Portugal 45% of mammals, birds, amphibians, and reptiles are associated with forests, particularly with deciduous and evergreen oak forest (Pereira *et al.*, 2005). Fires can also modify the balance of biotic interactions, e.g. by promoting predation in open areas (Letnic *et al.*, 2004) or favoring ruderals over stress-tolerant plants (Grime, 2001), and foster the invasion of disturbed areas by alien plant species (Keeley *et al.*, 2005)

As briefly described above, positive impacts of fire may be considered for some species or functional groups. Open habitat specialists can benefit from the increase of suitable areas, and birds of prey as well as many other predators will have increased opportunities for capturing prey (Santana *et al.*, 2012). Plant species adapted to transient nutrient flushes, including tall forbs such as *Digitalis purpurea* (Honrado, 2003), may also benefit from biomass breakdown and increased light availability promoted by low-intensity wildfires (Proença *et al.*, 2010). Landscape level plant diversity is promoted by wildfires in pyrodiverse landscapes, where differential fire spread on distinct vegetation types promotes landscape heterogeneity (Azevedo *et al.*, 2013).

1.3. Patterns and drivers of wildfires across scales

1.3.1. Historical data and the study of fire patterns across scales

Historical data have revealed that the occurrence of fires in Europe is not randomly distributed, with Southern Europe (i.e. the Mediterranean Region) being much more affected by the phenomenon (with 500 000 hectares burnt on average every year) than Northern and Central Europe (Yves Birot *et al.*, 2009).

The available data (European Fire Database; Camia *et al.*, 2010) highlight that the spatiotemporal distribution and recurrence of wildfires depend not only of climatic factors, but also of several other variables (e.g. land use and landscape structure, socio-economy and demography) which may affect this pattern at different levels of the phenomenon (Costa *et al.*, 2011). Recently, Yves Birot *et al.* (2009) attributed more than 90% of the ignitions in the Mediterranean basin to anthropogenic factors, which, when combined with the natural climatic conditions and hydric status of the vegetation, combustion and fire propagation, makes the southern European region clearly different from the rest of the continent (Pereira and Santos, 2003).

Previous studies have investigated the factors influencing long-term fire occurrence, fire danger and risk in Europe, from regional to local scales. At the European level, Sebastián-López *et al.* (2002) applied the fire potential index (FPI), an integrated index which combines long-term and short-term variables, to assess fire danger. Martínez *et al.* (2009) focused their research on the human factors of fire risk in Spain based on structural variables such as unemployment rate, average distance to roads and agrarian landscape patterns.

Sebastián-López *et al.* (2008) described a methodology to integrate socio-economic and environmental variables to model long-term fire danger in southern Europe, using stepwise regression. Koutsias *et al.* (2005, 2010) described results obtained with Geographically Weighted Regression in Southern Europe, using structural human variables in the model. At a local scale, Amatulli *et al.* (2006) applied classification and regression trees to assess long-term fire risk in a small area in the southeast of Italy. In Portugal, Nunes *et al.* (2005) and Carmo *et al.* (2011) used wildfire records to demonstrate fire selectivity regarding land cover types and topographic situations. These and other studies highlight the importance of historical wildfire data to assess the patterns of wildfires as well as their drivers.

1.3.2. Common causes of fire ignition

Wildfires start from a local epicentre (ignition point) and spread across landscapes mainly as a function of the abundance and arrangement of disturbance-susceptible patches (Turner *et al.*, 1989; Forman, 1997). The available European wildfire data show a clear geographic trend in the number of occurrences, with the majority of wildfires occurring in the southern countries (Yves Birot *et al.*, 2009). The total number of wildfires in this area has been increasing in the last decades (Pereira and Santos, 2003; European Commission, 2005), and the strictly natural causes for ignition are very rare. In fact, as much as 90% of the ignitions are related to human activities or behaviours (Yves Birot *et al.*, 2009). Nonetheless, extreme weather conditions, with high temperatures and dry winds, strongly dictate combustion and propagation conditions and therefore the final extension of the burnt area (Pereira and Santos, 2003).

In Portugal, the annual burnt area has considerably increased in the last three decades. In the period between 2003 and 2011, the average yearly burnt area was above 150 000 hectares, and the average number of occurrences was ca. 25 000 per year, well above Mediterranean European averages (European Commission, 2009). The relation of the total burnt area and the occurrence of a small number of large wildfires, in a small set of days with particularly favourable weather conditions, are particularly striking in Portugal (Pereira *et al.*, 2010). Recent assessments of probable causes for fire ignitions have revealed that in Portugal about 97% of all successfully investigated wildfires are human-caused (DGRF 2006). Common causes of fire ignition include: negligent usage of fire, accidental, structural causes, incendiary, natural and unknown (Lourenço *et al.*, 2013). In 2012 the National Guard proceeded with the criminal investigation of 15 404 forest fires (72.7% of the total registered in 2012). Intentional fires corresponded to 22% of the determined causes, and accidents or negligence were present in the ignition of 39% of all fires (Figure 1.3).

1.3.3. Determinants of fire behaviour

Constraints to fire activity due to vegetation and landscape differences, at scales from the biome to the local land cover patch, underline the importance of considering the ecological context when assessing the effects of climate variability on past and future wildfire activity (Litschert *et al.*, 2012). On average, Mediterranean Europe records 500 000 hectares of burnt land every year, with wildfires that surpass 50 hectares (only 2,6% of all wildfires) accounting for as much as 75% of the total burnt area (EFFIS, European Commission, 2009). Therefore, a small number of large wildfires actually determines the dimension of the losses in a given year (Strauss *et al.*, 1989), highlighting the importance of understanding fire behaviour across the landscape. Factors related to climate and weather conditions (temperature, wind, and relative humidity), local topography, vegetation and fuel conditions, land use and landscape structure, and socio-economic and demographic factors, are among those known to influence fire behavior (Chuvieco *et al.*, 2010).

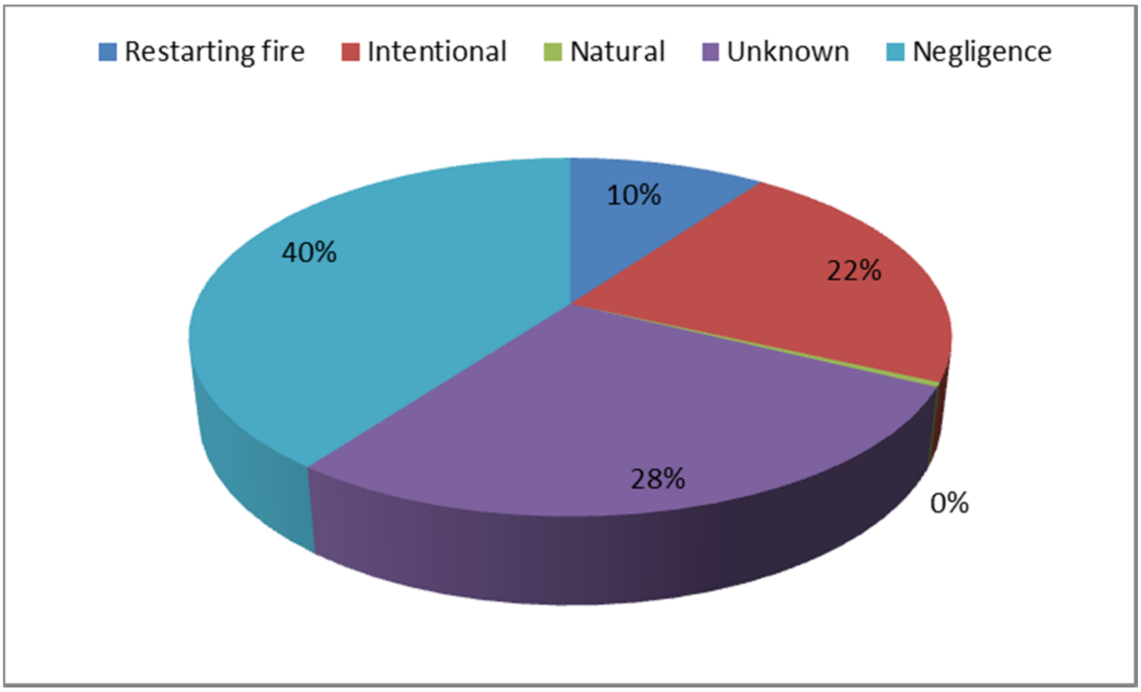


Figure 1.3 Main causes of forest fires in Portugal, in year 2012. Source: JRC (2012).

The relation between fire, climate and weather conditions is probably the best documented among all the factors and conditions considered in the study of the fire phenomenon. Weather conditions are known to affect fuel accumulation and moisture (e.g. Syphard *et al.*, 2008; Vilar *et al.*, 2010), thus having an effect on the probability of a fire to occur (Drever *et al.*, 2008; Bravo *et al.*, 2010; Moreno *et al.*, 2011). Moreover, certain climatic regimes (e.g. dry Mediterranean climates) are known to have promoted the evolution of plant strategies that very often include fire proneness (Mouillot *et al.*, 2005; Pausas *et al.*, 2012). Drought enhances wildfire potential in moist forest biomes where mean net primary productivity is relatively high and biomass is always available for burning, in contrast with xeric areas where the low productivity limits the availability of burnable fuels (Pausas and Bradstock, 2007; Archibald *et al.*, 2009; Littell *et al.*, 2009; Krawchuk and Moritz, 2011).

In Mediterranean areas, the role climate plays on fire occurrence is testified by, on one hand, the high wildfire seasonality, with a concentration of events during the dry and hot summer months (Keeley and Fotheringham, 2003; Pausas, 2004; Bajocco and Ricotta, 2008), and, on the other hand, by the strong correlation between the seasonal timing (i.e. phenology) of the vegetation (the major source of fuel) and the associated wildfire regimes (Bajocco *et al.*, 2010). These observations demonstrate a strong bioclimatic control over wildfire behavior, which is particularly important in Mediterranean regions where the anthropic component highly affects fire incidence patterns, both in terms of ignition sources and of fuel characteristics. This way it is easy to confound the relationships between fire behavior and natural pyrological conditions (Vazquez *et al.*, 2002).

The effects of future climate change on altering fire regimes are still a matter of debate (Flannigan *et al.*, 2000; Dube, 2009). In an analysis of climate scenarios for Portugal, Santos *et al.* (2002) reported a general trend towards an increase in mean annual surface air temperature from 1972 until 2000. For precipitation, although changes in the annual mean are not evident, a systematic reduction in spring precipitation in all stations of continental Portugal was observed for the period 1931-2000 (Santos *et al.*, 2002). A climatic shift towards more frequent dry periods and seasonal precipitation shifts in the Mediterranean (Giorgio and Lionello, 2007) are expected to interact with socioeconomic and landscape factors in determining the number of fires (Filipe *et al.*, 2009). Extreme climatic events are also very important. In 2003, during the heat wave, a record number of large wildfires were observed in European countries (Barbosa *et al.*, 2003). In Portugal, the burnt area was more than twice the previous extreme (1998) and four times the 1980-2004 average (Trigo *et al.*, 2006). As a result, 8.6% of the total Portuguese forest area was burned leading to an economic impact exceeding one billion euros (De Bono *et al.*, 2004). In Greece, the 2007 unusual extent of forest fires exposed the vulnerabilities of fire defense mechanisms when multiple ignitions and favorable climatic conditions occurred simultaneously (Xanthopoulos, 2007).

The spatiotemporal variability of climate conditions and the heterogeneity in vegetation and fuel load play an essential role in determining fire behavior and severity throughout the landscape. In fact, differences among fuel types can modulate fire-climate relationships at a regional scale (Pausas and Paula, 2012) and even at local scales (Gartner *et al.*, 2012). In forests that once experienced frequent, low to moderate intensity fire regimes, reduction of surface and ladder fuels can create forests with high resistance to wildfires (van Wagtendonk, 1996; Agee and Skinner, 2005; North *et al.*, 2007; Stephens *et al.*, 2009).

If the different vegetation types were all equally fire-prone, then fires would occur randomly across the landscape. Actually, certain vegetation types are more (or less) fire-prone than others; they can thus be considered as ‘preferred’ (or ‘avoided’) by fire. In this view, fire can be regarded as acting like an ‘herbivore’ that positively (or negatively) selects different resources (i.e., vegetation types). When a resource is consumed by fire disproportionately with respect to its availability, then fire behavior is considered 'selective' (Nunes *et al.*, 2005; Bajocco and Ricotta, 2008). To date, most studies on fire selectivity focused on the relationship between wildfire patterns and the structural features of the landscape like land cover categories (Stolle *et al.*, 2003; Nunes *et al.*, 2005; Bajocco and Ricotta, 2008) and vegetation types (Cumming, 2001; Pezzatti *et al.*, 2009), while the functional characteristics of the landscape like land degradation, vegetation productivity or fuel phenology are only rarely considered (Bajocco *et al.*, 2011). As the phenological status of vegetation represents a primary driver influencing fuel characteristics, regarding both fuel availability and moisture content, fire monitoring and prediction over large areas requires the capability of capturing broad-scale changes in vegetation phenology that are descriptive of changes in fuel conditions (Angelis *et al.*, 2012).

In fact, considering the functional characteristics of the landscape allows adding a dynamic component to wildfire analyses. This functional approach is particularly useful when dealing with global change issues, since knowing the relations between fire and vegetation dynamics may help predicting future fire behavior under different climatic and environmental scenarios (Bajocco *et al.*, 2010a). Vegetation phenology (i.e., the influence of climatic variables on the timing of plant development stages) plays an important role in fire studies (Bajocco *et al.*, 2010a; Akther and Hassan, 2011). Remotely sensed observations derived by sensors like MODIS provide comprehensive spatial coverage (from 250 m to 1 km of pixel-size) and enough temporal resolution (16-days composites of daily images) to update fuel conditions in a more efficient and operational manner than traditional aerial photography (Oswald *et al.*, 1999) or fieldwork (Riano *et al.*, 2002). Furthermore, they are particularly useful for investigations of wildfire history (Hicke *et al.*, 2003), fuel load production (Roberts *et al.*, 2003), and impact of land use on fuel load (Bachelet *et al.*, 2000). The Normalized Difference Vegetation Index (NDVI) has been used for fire risk estimation in the Mediterranean region by Gabban *et al.* (2006) and by Cheret and Denux (2007), and in northern boreal forests by Leblon *et al.* (2001). Newnham *et al.* (2011) used NDVI for assessing curing of grassland fuel, and the harmonic analysis of NDVI time series was used by Bajocco *et al.* (2010) to investigate fire incidence probability. A review of fire assessment through remote sensing techniques (particularly high spatial and/or temporal resolution imagery) in the context of conservation monitoring can be found in Nagendra *et al.* (2012).

Topographic features are also often considered in fire risk assessments and in a variety of studies regarding fire patterns. Variations in topography have been shown to affect vegetation distribution, composition and flammability (Syphard *et al.*, 2008; Whelan, 1995). Topography directly affects fire behavior by promoting radiant energy transfer from the fire line towards the higher slopes (Rothermel, 1983). Indirectly, topography also affects fire by creating different microclimates, which influence the moisture content of fuels, air temperature, wind patterns, as well as the distribution of plant species across the landscape (Heyerdahl *et al.*, 2001; Mermoz *et al.*, 2005). Topography and land cover are often linked, e.g. agricultural areas may be preferentially located in lowland plains and forests in slopes, which may hinder the understanding of the ultimate drivers of fire spread. Over larger areas and at coarser scales, elevation gradients and topography are also correlated with climatic patterns (Mesquita *et al.*, 2009).

Land use and landscape structure represent a synthesis between environmental (biophysical) and human influences on the spatial and temporal distribution of conditions, resources and disturbances (Farina *et al.*, 2006). Landscape composition and configuration have often been associated with fire occurrence (e.g. Syphard *et al.*, 2008; Catry *et al.*, 2009; Martínez *et al.*, 2009; Vilar *et al.*, 2010; Azevedo *et al.*, 2013), based on the analysis of land cover maps in which vegetation types are used as proxies for fuel types and express the interaction with human influences (Nunes *et al.*, 2005; Moreira *et al.*, 2011). Fire spread rate can be facilitated or retarded by landscape heterogeneity (Turner and Dale, 1990). Thus, the spatial patterns of fire ignition and spread across landscapes are affected by fire proneness, i.e. the differential fire behavior in various land cover types that are not equally fire prone (e.g. Bajocco and Ricotta, 2008; Moreira *et al.*, 2009). The type of vegetation that differentiates each land cover type has a key role, considering its fuel structure, load and moisture content (Turner and Dale, 1991; Bajocco and Ricotta, 2008; Moreira *et al.*, 2009). Fires are usually selective for, and grow larger in, less pyrodiverse landscapes (Viedma *et al.*, 2009; Loepfe *et al.*, 2010).

Much attention has been given to the relationship between landscape structure and characteristics of fire, including severity and spread (Bajocco and Ricotta, 2008; Kerby *et al.*, 2007; Ryu *et al.*, 2007; Wimberly and Reilly, 2007). From a landscape ecology perspective, landscape structure includes two dimensions: composition and configuration (McGarigal and Marks, 1995; Turner *et al.*, 2001). Both aspects are strongly tied to many characteristics of fire such as spread, severity, fuel types, and fuel loading (Lloret *et al.*, 2002; Gonzalez *et al.*, 2005; Nunes *et al.*, 2005; Kerby *et al.*, 2007). Ryu *et al.* (2007) investigated the relationship between burned area of the Washburn Ranger District of the Chequamegon National Forest, Wisconsin, United States, and landscape structure using spatial pattern metrics including, among others, mean patch size, mean shape index, and Shannon's diversity index. They reported a strong tie between burned area and landscape structure and concluded that, to mitigate fire spread, the forest landscape should be composed of numerous, small, irregularly shaped patches of different types of forests.

Several studies have pointed out that demographic and socio-economic factors are also key influences on fire history in several regions (Martínez *et al.*, 2009; Catry *et al.*, 2009; Chuvieco *et al.*, 2010; Koutsias *et al.*, 2005). Variables such as unemployment rate, average distance to roads, or population density, as well as their recent dynamics, have been used to account for fire patterns and trends (Turner *et al.*, 2008; Martínez *et al.*, 2009; Ribeiro *et al.*, 2009). Landscape changing processes such as agricultural intensification or abandonment, deforestation, fire suppression, livestock grazing or urban development (Farina, 1998) are mostly determined by socioeconomic and political issues. These alterations, combined with the increase of ignition sources related to high population densities in rural–urban interfaces, have greatly expanded in the Mediterranean region over the last decades (Silva *et al.*, 2010).

1.4. Post-fire resilience and its drivers across scales

1.4.1. Features of wildfires and fire regimes

Disturbances can be characterised by a number of features, which are commonly used in "disturbance ecology" (Turner *et al.*, 2001). *Intensity* describes the physical energy released by the disturbance in a given area and time period, whereas *severity* expresses the effects of the disturbance on the ecological system. In contrast, *size* expresses the area or spatial extent affected by a given disturbance event. These and other features (e.g. shape and ecological heterogeneity of the area affected) can be used in fire ecology to describe individual wildfires (Miller *et al.*, 2012).

Wildfire regimes are usually characterized using descriptive statistics from the set of fire events occurring in a given area and time period (e.g. mean or median intensity, severity or size (Jiang *et al.*, 2009). Another very important feature of fire regimes is *frequency*, which is the mean or median number of events occurring at one point in a given time period; the *return interval* is the mean time distance between consecutive events, and it is therefore the inverse of the frequency (Turner *et al.*, 2001). The features of regional fire regimes can be summarized under the concept of *pyrodiversity*, which describes the variability in frequency, intensity, seasonality and dimensions of fire patterns across that landscape (Martin and Sapsis, 1991; Faivre *et al.*, 2011).

Describing the features of wildfires and fire regimes as well as understanding their determinants if of high importance since they have a direct influence on their ecologic and socio-economic impacts, as well as in the resilience of (social-)ecological systems after disturbance by fire. This will be addressed in more detail in the next sections.

1.4.2. Resilience in the context of fire disturbance

Resilience is a property of ecosystems which describes their capacity to recover to the initial condition after a disturbance event, whereas *resistance* expresses the capacity of ecosystems to resist undergoing changes when affected by a disturbance (MacGillivray and Grime, 1995; He and Mladenoff, 1999; Díaz-Delgado *et al.*, 2002; Brown *et al.*, 2004; Pausas *et al.*, 2004). The concept of post-fire resilience has been thoroughly explored in the scientific literature (e.g., MacGillivray and Grime, 1995; He and Mladenoff, 1999; Díaz-Delgado *et al.*, 2002; Brown *et al.*, 2004; Pausas *et al.*, 2004). Post-fire resilience can be measured from a wide array of system state variables, related to vegetation structure (Lee *et al.*, 2009), biodiversity and community structure (e.g. Kazanis *et al.*, 2004; Pausas *et al.*, 2008; Moreira *et al.*, 2011) or ecosystem functioning (e.g. Bajocco and Ricotta, 2008; Silva *et al.*, 2011). Wildfires can cause dramatic changes in most variables of ecosystem state as well as in their rate of recovery to the initial state, depending on fire intensity and frequency among other factors (Pausas, 2008, 2012; Lee *et al.*, 2009).

Fire has a complex effect on vegetation regeneration, mainly due to differential responses of plant species and vegetation types to wildfires and fire regimes (Wittenberg *et al.*, 2007; Groeneveld *et al.*, 2008). According to Keely *et al.* (2005) there are four main hypotheses establishing that post-fire recovery patterns are mainly determined by: (1) fire severity and post-fire fluctuations in precipitation (“event-dependent hypothesis”); (2) length of the fire free period, which affects reproductive success/failure and fuel accumulation (“fire interval hypothesis”); (3) internal density-dependent control, which regulates the shift from herbs to woody species (“self-regulatory hypothesis”); and (4) extrinsic environmental factors that vary spatially across the landscape (“environmental filter hypothesis”).

1.4.3. Plant functional ecology and post-fire regeneration strategies

Plant species survival in ecosystems after major disturbance events is largely dependent on their ability to recover after biomass destruction (Cornelissen *et al.*, 2003). Post-fire regeneration is favored by nutrient increase from ashes and by stronger light availability allied to the absence of competitors (de Bano and Conrad, 1978; Tyler, 1996; Clemente *et al.*, 2005), which then influence species abundance, dominance and evenness (Marzano *et al.*, 2012).

Plant species may regenerate by distinct processes, such as resprouting, clonality and seedling recruitment (Menges and Kohfeldt 1995; Maguire & Mendes, 2011). These post-fire regeneration modes are mostly dependent on recruitment and resprouting, which are determined by species life history. A close relation may be expected between regeneration and local seed bank features in the case of seeder plants (Ne’eman *et al.*, 2009), whereas regenerative processes involving resprouting will depend on an adapted root system that can ensure water and carbohydrate provision for the development of new shoots. Therefore different regeneration strategies, resprouting and seeding, with diverse ecological conditions and dependencies to nutrient and water provision, may be identified (De Souza *et al.*, 1986; Hastings *et al.*, 1989; Castell *et al.*, 1994; Fleck *et al.*, 1995; Clemente *et al.*, 2005). However, regenerative traits may covary with other functional attributes more related with resource uptake and stress tolerance, hampering the ability to understand the role of individual traits as fundamental driving forces in post-fire regeneration (Clemente *et al.*, 2005).

Resprouter species develop new sprouts, whereas seeders regenerate by seed germination from local seed banks or nearby populations, which are due to change with fire and biogeography (Clemente *et al.*, 2005; Lloret *et al.*, 2005). There are important ecological trade-offs determining sprouting and non-sprouting species (Cornelissen *et al.*, 2003). An example is provided by drought resistance, with resprouters usually revealing lower drought resistance and lower efficiency in water consumption (Krivtsov *et al.*, 2009). The ability to resprout is a tolerance functional binary trait (resprouters vs. non-resprouters), contributing to persistence and stabilization of plant populations, and is dependent on bud and shoot location after a fire event (Pausas *et al.*, 2004; Nano & Clarke, 2011; Clarke *et al.*, 2013). Resprouting species can inhabit the same locations throughout time allowing some stability of ecosystem and landscape pyrodiversity (Clarke *et al.* 2010; Maguire & Mendes, 2011).

Seeding mechanisms have evolved along with the Mediterranean climate and fire patterns, and they are a product of the fire selective pressure towards faster germination and seedling establishment (Pausas and Verdu, 2006; Saura-Mas and Lloret, 2007; Keeley *et al.*, 2012; Santana *et al.*, 2013). Moreover, certain physiological attributes are known to be related to a seed dormancy breakage by high summer temperatures, thereby allowing seedlings to evade summer drought, which is the most significant factor constraining seedling establishment (Baskin & Baskin, 1998; Pausas *et al.*, 2006; Baeza and Roy, 2008; Santana *et al.*, 2013). In Mediterranean landscapes, seedling drought tolerance and growth ability are important factors after fire events, with likely effects on community composition, since distinct drought tolerance among seeders will provoke differential survival (Frazer and Davis, 1988; Davis, 1989; Moreno and Oechel, 1992; Clemente *et al.*, 2005). Moreover, seeders persistence may become threatened by future changes in fire regimes (Verdú *et al.*, 2007; Marzano *et al.*, 2012).

The adaptive attributes of species to environmental modifications can be assessed through the use of functional traits (Moretti *et al.*, 2009). Ecosystem and landscape vulnerability to wildfires may be increased by the loss of plant species bearing resilience-related traits (Eriksson, 2000; Dale *et al.*, 2001; Buma and Wessman, 2012). In disturbed ecosystems, the inclusion of species life forms and history, as well as response strategies, may help to identify those species, strategies or functional groups that are key to improve models of ecological response (Syphard and Franklin, 2010). Traits related to water availability or carbon storage and associated to regeneration strategies are among those most studied in Mediterranean ecosystems (Ackerly, 2004). Since fire regimes and land use history are critical factors to understand the structure and dynamics of Mediterranean landscapes, it is important to assess how those factors may interact with functional diversity, since the abundance and diversity of functional groups are driven by landscape processes, with fire regime as a key component of the system (Lloret and Vilà, 2009).

Several examples illustrate the use of functional diversity in wildfire ecology. Llloret and Vilà (2009) have looked at the diversity of plant functional types (PFTs) by growth forms and regenerative attributes related to fire disturbances; PFTs contributed to a deeper comprehension of landscape ecological processes through the identification of response groups of species with common key traits (Lavorel *et al.*, 1997; McIntyre *et al.*, 2001; Lloret and Vilà, 2009). Using functional traits, Syphard and Frankly (2010) were able to find differences in predictive accuracy revealed by changes in the patterns of species life history, rarity and disturbance responses, considering important ecological processes and patterns such as dispersal mechanisms or species prevalence. Combinations of animal and plant traits were also applied to demonstrate a close relation between those traits and ecological limitations induced by fire (Figure 1.4) (Moretti *et al.*, 2009).

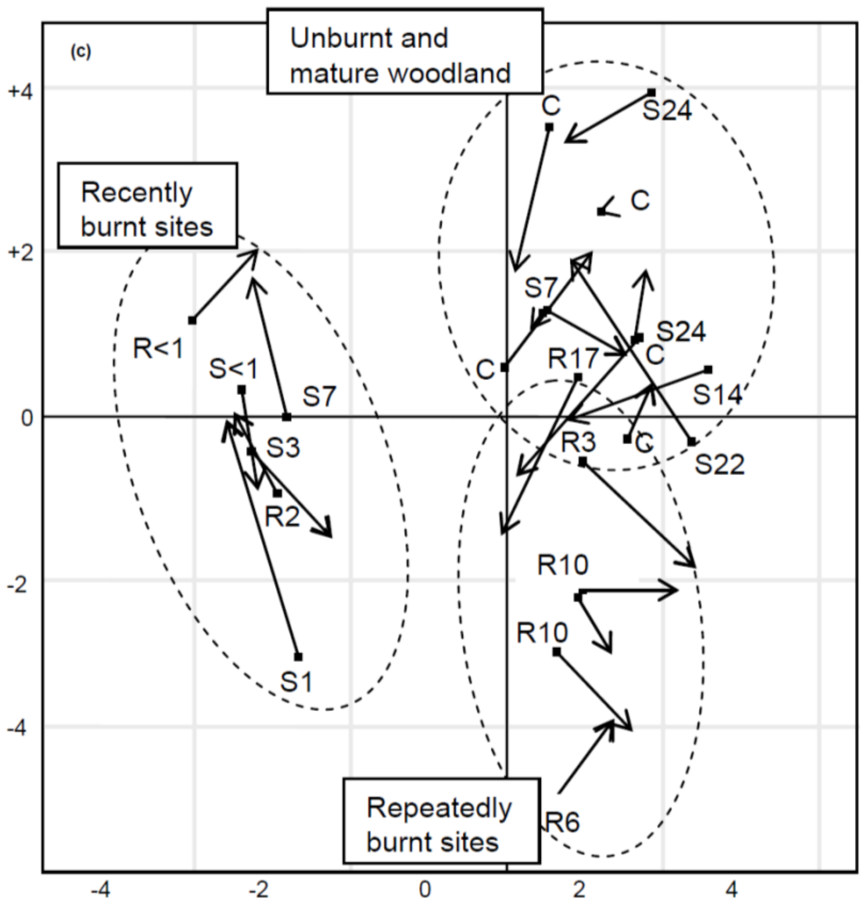


Figure 1.4 Plant traits (base of arrow) and animal traits (head of arrow) ordination of sample sites in a study of plant and animal traits to assess community functional responses to disturbance in Switzerland. Note that short arrows indicate that the plant and animal traits occupy similar positions in the ordination space; (S =single fire site; R =repeated fires site; the number indicates the number of years elapsed since the last fire; C = control sites, unburnt for at least 30 years). Source: Moretti *et al.* (2009).

1.4.4. Factors determining vegetation resilience to fire disturbance

From the above sections, post-fire vegetation resilience can be influenced by a wide range of factors, including features of wildfires and fire regimes, abiotic conditions, biotic traits and processes, and landscape processes (Díaz-Delgado *et al.*, 2002).

Features of wildfires and fire regimes such as intensity, severity and frequency can strongly determine the rate of vegetation recovery after fire. In general, fires that are more intense, severe and/or frequent will induce more damage on vegetation and on other components of ecosystems (e.g. soil), thereby hampering their ability to exhibit high rates of recovery after those disturbance events (Pereira *et al.*, 2005; Malvar *et al.*, 2010).

Abiotic conditions are also of high importance for post-fire regeneration. Recovery rates are usually higher in areas of high intrinsic productivity, which are generally related to benign environmental conditions (Navarro, 2011; Malkisnon *et al.*, 2012). Effects of abiotic factors on vegetation resilience have been reported for climate (e.g. Syphard *et al.*, 2008; Vilar *et al.*, 2010), topography/terrain morphology (e.g. Whelan, 1995; Syphard *et al.*, 2008), soil types or properties (e.g. Maia *et al.*, 2012), and geology (Smit *et al.*, 2012).

Post-fire vegetation resilience is also much influenced by biotic traits and processes, such as pre-fire community structure, seed bank condition after fire, invasion by alien species, and several types of biotic interactions. Disturbance and succession are two forces working in opposite directions, and as a consequence of fire events the landscape becomes an heterogeneous mosaic of patches with different burning histories (Turner *et al.*, 2011). In Mediterranean ecosystems, at least part of the vegetation has developed resprouting abilities or seed bank persistence, so the high wildfire recurrence and the rapid vegetation recovery make Mediterranean mosaics highly dynamic (Trabaud *et al.*, 1996; Dìaz-Delgado and Pons, 2001), eventually contributing to enhance their biodiversity (Keely *et al.*, 2005).

The relation between wildfire and anthropogenically maintained grazing landscapes is ancient and can assume different degree of sustainability (Ruiz-Mirazo, 2012). Tall scrub formations that periodically experience top-kill by crown fires are particularly susceptible to browsing by cattle and other mammalian herbivores because the vegetation that usually matures above the browsing line is temporarily within reach for herbivores during the regeneration phase (Quinn, 1986).

Stand-replacing crown fires are a recurrent disturbance in the scrublands of the Mediterranean. Following a fire, dominant species of tall shrubs rapidly recapture their pre-fire dominance without significant local extinction or invasion of pioneer species, in a process known as auto-succession (Hanes, 1971; Keeley *et al.*, 2012). Although Mediterranean tall scrub communities typically display resilience to periodic wildfire, the auto-succession process may fail when the fire-return intervals are too short, under which vegetation can shift from a closed canopy to an open canopy dominated by monotypic vigorous resprouters, disturbance dependent scrub species, and exotic grasses and forbs (Zedler *et al.*, 1983; Stylinski and Allen, 1999; Jacobsen *et al.*, 2004).

Seed banks accumulated in the upper soil layers are known to have a transient nature and a strong influence of fire (Ferrandis *et al.*, 2001). Some Mediterranean species, such as *Cistus ladanifer* and *C. salviifolius*, have shown dormancy in the absence of fire, and low to medium intensity fires do not influence their germination rates (Ferrandis *et al.*, 1999). In general, recurrent wildfires have a selective impact on the soil seed bank: species with transient seed reserves are eliminated whereas those with persistent, buried seed reserves tend to remain in the soil after the fire (Ferrandis *et al.*, 1999). Several authors defend that a more diverse set of species should be included in plantation and restoration plans to improve landscape resilience to current fire regimes (Pausas *et al.*, 2004; Vallejo *et al.*, 2006).

Landscape processes related to the spatial patterning of vegetation and other land cover types can play an important role in post-fire regeneration patterns and rates (Moreira *et al.*, 2011). Habitat fragmentation and limitations to organism mobility and dispersal, expressing on modified metapopulation and metacommunity dynamics, are examples of landscape processes that may affect post-fire regeneration (Miller *et al.*, 2012) while at the same time influencing the spread of other pressures and disturbances such as diseases or invasive species (Keeley *et al.*, 2005).

Landscape patterns/configuration and wildfires are mutually dependent, as land cover patterns can influence burning patterns through the spatial arrangement of flammable biomass (Nunes *et al.*, 2005), whereas the spatial heterogeneity of fire patterns may influence a variety of ecological processes and the post-fire distribution of biomass (Berner *et al.*, 2011), thereby also influencing vegetation recovery rates. Landscape structure is closely associated with post-fire vegetation composition and configuration, including plant regeneration and plant mortality (Brown, 2000). Therefore, understanding the relationship between landscape structure, fire characteristics and post-fire regeneration is critical, not only for managing ecosystems and landscapes towards improved resistance to fire ignition and spread, but also to enhance the recovery of ecosystems in burned areas (Moreira *et al.*, 2011).

1.4.5. Assessing vegetation resilience at regional and local scales

Post-fire vegetation resilience can be assessed at regional or local scales, usually with distinct objectives and based on different methods, tools and data sources. Regional assessments are most important for spatial planning and risk mitigation across large areas, whereas local surveys are particularly relevant in the context of local resource management and post-fire restoration projects (Veblen, 2002).

Regional patterns of post-fire resilience can efficiently be analysed with remote sensing tools. From a wildfire analysis perspective, remote sensing of vegetation offers comprehensive spatial information about fuel type, fuel properties, and fuel condition (Schneider *et al.*, 2008). Accordingly, several parameters related to fire occurrence, such as fuel moisture, fuel curing and several fire risk indices have been analyzed using remote sensing variables like greenness or wetness indices (Stow *et al.*, 2005; Roberts *et al.*, 2006; Akther and Hassan, 2011; Newnham *et al.*, 2011). Diaz-Delgado (2002) used the Normalized Difference Vegetation Index (NDVI) from Landsat imagery to monitor vegetation recovery after successive fires, correlating fire recurrence to regeneration capability and to the contribution of different plant life strategies to resilience.

Leeuwen *et al.* (2010) used land surface phenological metrics, including the start and end of the season, the base and peak NDVI, and the integrated seasonal NDVI, to monitor post-wildfire vegetation response with remotely sensed time-series data in Spain, USA and Israel. Their results suggest that a monitoring approach based on readily available satellite-based time-series vegetation data can provide a valuable tool for assessing post-fire vegetation responses.

Measuring local patterns of resilience can be based on in-field surveys to detect changes in vegetation and community structure (Huffman *et al.*, 2012). These surveys may include a whole small system (e.g. in cases of post-fire responses in a small burnt area) or cover a larger area and then be based on a statistical sampling design. At each location post-fire regeneration can be estimated from repeated measurements of parameters related to vegetation structure (e.g. canopy cover, height and cover of understory strata; Huffman *et al.*, 2012) and/or to community structure (e.g. species richness and composition, functional diversity, or seedling and resprouting rates; Proença *et al.*, 2010). Post-disturbance succession and resilience can also be assessed from comparative studies of areas with different time distances to disturbance events, in which the spatial sampling design is actually expressing a temporal gradient (McPherson and DeStefano, 2003; Santana *et al.*, 2011).

1.5. Thesis objectives and outline

1.5.1. General context and overarching research goals

Wildfires are a key driver of ecological change, particularly in regions with medium to high productivity and a strong seasonal distribution of annual rainfall. In the Mediterranean countries of Southern Europe, thousands of hectares are burnt every year, particularly during the dry summer period (JRC, 2012). Wildfires are among the hazards that cause higher ecological and economical damage, as well as the loss of human lives, and much effort has been put in the development of tools to accurately predict the spatial and temporal patterns of wildfire occurrence in an attempt to promote prevention as well as to improve fire fighting (Finney and Mark, 2004; Key *et al.*, 2006).

In Portugal, although changes in fire regimes were noted over the past two decades (Pereira *et al.*, 2005), the relative importance of human activities and climatic variability to explain regional fire statistics remains insufficiently understood (Carvalho *et al.*, 2008). In spite of being the smallest of the five western Mediterranean countries, Portugal is the most affected by fire, regarding both the number of fire events and relative burnt area. From 1980 to 2004, an area equivalent to 30% of the country was burnt. The closest cases (Italy and Spain) present values of fire occurrence, density and burnt area inferior by 1/3 and 1/5, respectively (Pereira *et al.*, 1998; Pereira and Santos, 2003; European Commission, 2005). In this context, it is of key importance for national authorities to understand and anticipate the patterns of fire ignition and propagation, in order to effectively promote fire control policies and preventive landscape management. As ignitions are, most often, typically related to anthropogenic causes (Guyette *et al.*, 2002) and will likely keep occurring in the future, studies of fire patterns have been concentrated in the assessment of the more suitable conditions for a fire to spread over the landscape (Moreira *et al.*, 2012).

In recent years, research about the spatial and temporal distribution of fires, as well as its causes and drivers, has involved analyses of national or regional wildfire statistics (Moreira *et al.*, 2011). In environmentally and socio-economically heterogeneous countries one could expect to observe contrasting fire patterns depending of the region and of its biophysical and socio-economic characteristics (Venn and Calkin, 2008). In Portugal, such regional variations in number, extent and severity of wildfires are well known and have been successively reported (Carmo *et al.*, 2011; Moreira *et al.*, 2001, 2010, 2011; Silva *et al.*, 2011). Nonetheless, the effects of these reports on improving fire risk management, from preventive landscape management to firefighting planning, have so far been modest, probably due to the lack of solid causal or correlative relationships with regional conditions and socio-economy (Martínez *et al.*, 2009; Moreira *et al.*, 2009). In heterogeneous countries the analysis of this type of spatial pattern in the size and number of fires calls for a regional approach to the problem, since the prominent factors in fire history may be quite different for contrasting regions across the country.

On the other hand, from an ecological perspective wildfires are considered one of main types of disturbance in ecosystems and landscapes, potentially driving profound changes in their structure, composition and functioning (Robinson *et al.*, 2013). Resilience to natural and human disturbances is a key property of ecosystems whose determinants across scales are not fully understood. The study of ecosystem resilience after fire disturbance events has nonetheless been a subject of fire ecology research (e.g. Lavorel 1999; Díaz-Delgado *et al.*, 2002; Pausas *et al.*, 2009), due to its importance for impact mitigation and restoration as well as for the provision of valuable ecosystem and landscape services such as soil erosion control, carbon sequestration and water regulation.

In this context, two overarching goals were defined for the research developed for this thesis:

(1) to analyse, model and interpret the spatiotemporal patterns of wildfire occurrence at several scales in an heterogeneous country, and
(2) to analyse, model and interpret regional and local patterns of post-fire vegetation resilience using complementary approaches and data sources (remote sensing and in-field surveys).

These two goals were addressed at regional (whole country and its North region), sub-regional and local spatial scales in Portugal, the Mediterranean country of Europe most heavily affected by wildfires (Pereira *et al.*, 1998; Pereira and Santos, 2003; European Commission, 2005).

1.5.2. Specific objectives and research questions/hypotheses

The research presented in this thesis was thus organized around those two general, overarching goals, each one assessed according to two specific research questions, for a total of four studies (Table 1.1):

1) Identifying the main factors driving the occurrence of wildfires in different spatial scales and contexts, as well as their relative importance, by addressing the following questions:
   a) Which factors most contribute to explain the patterns of wildfires in Portugal, an environmentally heterogeneous country? Are those factors different for the several

regions in the country?

b) Which factors most contribute to explain the patterns of wildfires in the Alto Minho, an environmentally heterogeneous sub-region in Portugal?

2) Identifying the main factors driving the patterns of post-fire ecosystem resilience at different spatial scales, as well as their relative importance, by addressing the following questions:

   a) Which factors most determine post-fire regeneration of ecosystem functioning after fire disturbance in a regional context (North of Portugal)? Are those factors different for distinct regeneration indicators?

   b) Is there a significant effect of geological setting and fire history, in otherwise environmentally homogeneous areas, on the local patterns of post-fire regeneration of early successional vegetation?

Table 1.1 General overview of the research outline and its relation with the research objectives, questions and spatial scales.

Multi-scale assessment of patterns and drivers of wildfires and post-fire resilience		**Spatial scales of assessment**		
		Regional	Sub-regional	Local
1. Patterns and drivers of wildfires	**1a.** Modelling wildfire patterns and its drivers in continental Portugal	✓		
	1b. Modelling wildfire patterns and its drivers in the Alto Minho sub-region		✓	
2. Patterns and drivers of post-fire resilience	**2a.** Assessing the patterns and drivers of post-fire functional resilience	✓		
	2b. Assessing the patterns and drivers of post-fire structural resilience			✓

1.5.3. Outline of the thesis

Based on the research objectives and questions outlined above, this thesis is organized around the assessment of the patterns and drivers of wildfire occurrence and post-fire resilience at several spatial scales, as depicted in Table 1.1. The thesis follows a classical structure and therefore it is generally organized in four chapters:

(1) an Introduction chapter, in which the theoretical context and the objectives of the research performed for the thesis are described (chapter 1);

(2) a Methods chapter, in which the study areas as well as the main datasets, data collection techniques and analytical frameworks are described (chapter 2);

(3) a Results chapter, where the main results developed under the four research questions are described and briefly discussed (chapter 3);

and finally

(4) a Discussion and Conclusions chapter, in which a detailed and integrative discussion of the results described in the previous chapter is provided and the main conclusions are outlined (chapter 4).

Four studies were performed under this framework (see Table 1.1). The first two studies, developed under research objective 1, are devoted to the analysis of spatiotemporal patterns of wildfire occurrence at regional and sub-regional scales in continental Portugal. Using two distinct modeling frameworks, the factors underlying the historical occurrence of wildfires were analysed for the whole country and its agrarian regions (research question 1a) and in the Alto Minho sub-region (question 1b). A particular attention was devoted to assessing the relative importance of abiotic conditions, socio-economic and demographic factors, and land cover/use and landscape structure, to explain the patterns of wildfires.

Two other studies addressed regional and local patterns of post-fire ecosystem resilience, under research objective 2. Under question 2a, we used remote sensing techniques to assess regional patterns of ecosystem functional resilience after fire and to identify its determinants in the North of Portugal. Finally, to address question 2b, we developed a geologically-stratified random sampling of burnt areas, also differing in fire frequency and time distance to last fire, in which we surveyed vegetation structure and plant community structure to infer upon the factors controlling local regeneration after fire in early successional vegetation.

2. Methods

This chapter describes the datasets, the pre-processing methods and the modelling frameworks used in this thesis. It is organised as three sequential sections describing the study areas addressed in the several studies (2.1), the key datasets used and the associated (pre-)processing routines (2.2), and finally the statistical modelling methods and the analytical framework for each study (2.3).

2.1. Study areas

In the development of this research of the patterns and drivers of wildfires and post-fire resilience, the analyses were focused on four nested test areas in Portugal (Figure 2.1):

(1) the whole Portuguese mainland, corresponding to a regional spatial scale (country level);

(2) the Northern part of the country, also corresponding to a regional spatial scale (region level);

(3) the Alto Minho region, nested in the North of Portugal (regional scale, sub-region level); and

(4) the Baixo Tâmega mountains, also nested in the north of Portugal (local scale, municipality level).

The study areas are located within the Iberian Peninsula, which is considered to be a very dynamic area in relation to global change and ecosystem functioning (Alcaraz-Segura *et al.*, 2006). These four areas are described in the sections below, with an emphasis on those factors potentially more related with patterns of wildfires and/or post-fire resilience.

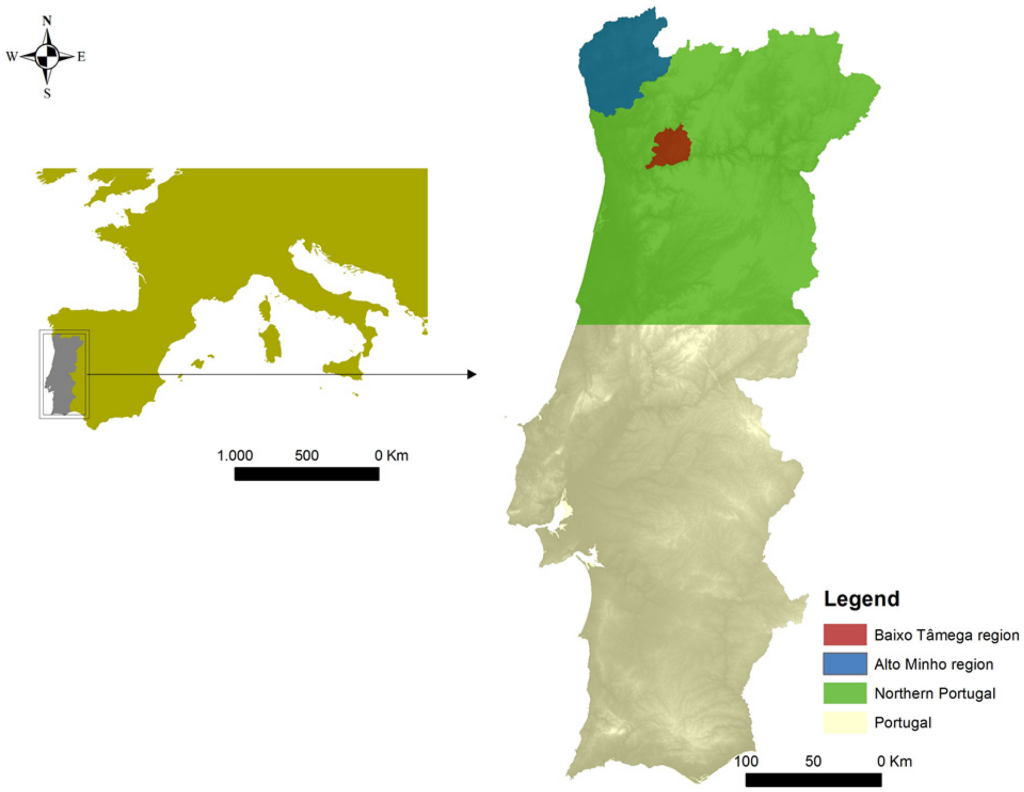


Figure 2.1 The four study areas in mainland Portugal: location in the Iberian/European context and geographic relations among them.

2.1.1. National level: Continental Portugal

2.1.1.1. Location and abiotic conditions

The study area to address national patterns of fire occurrence was the entire Portuguese mainland, which covers ca. 90 000km^2 at the southwest end of Europe (Figure 2.1), located between 36º57`N and 42º09`N latitude and between 6º11´W and 9º30´W longitude.

Most of the country is included in the Mediterranean biogeographic region, with a Mediterranean type of climate (i.e. with a dry season corresponding to the summer period), and only the north-western corner belongs to the Eurosiberian region, with an Atlantic type of climate (Costa *et al.*, 1998; Figure 2.2, left). In the global climatic classification of Metzger *et al.* (2012), most of mainland Portugal has Warm Temperate climate, xeric to mesic, with cold and wet conditions being reached in the main mountain tops Figure 2.2, right).

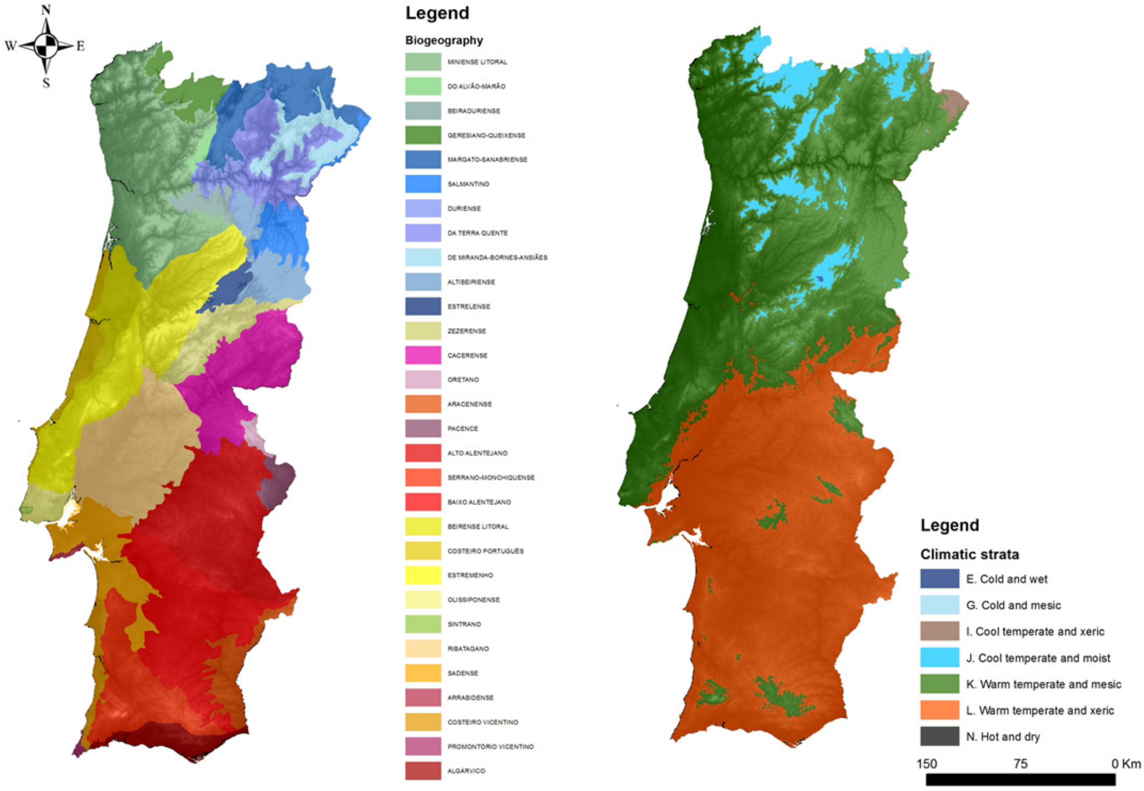


Figure 2.2 (left) Biogeographic map of mainland Portugal at the sector level; areas with Atlantic climate and vegetation are represented in green; (right) Climatic strata in mainland Portugal, according to a global climatic stratification. Sources: (left) Costa *et al.* (1998), (right) Metzger *et al.* (2012).

Elevation in mainland Portugal ranges from sea level along the coast up to 1993m in the top of the Serra da Estrela, with most of the mountainous and high plateau areas concentrated in the northern half of the country (Figure 2.3, top left). Schist and granite are the predominant bedrock types, with limestone and other sedimentary formations strongly represented in the centre-west and southwest areas (Figure 2.3, top right).

Mean annual temperatures range from ca. 7ºC in the northern elevations to ca. 18ºC in the southern lowlands (Figure 2.3, bottom left). Mean total annual precipitation ranges from ca. 400mm in the southern areas and in the upper Douro valley up to ca. 2800mm in the northwest mountains (Figure 2.3, bottom right).

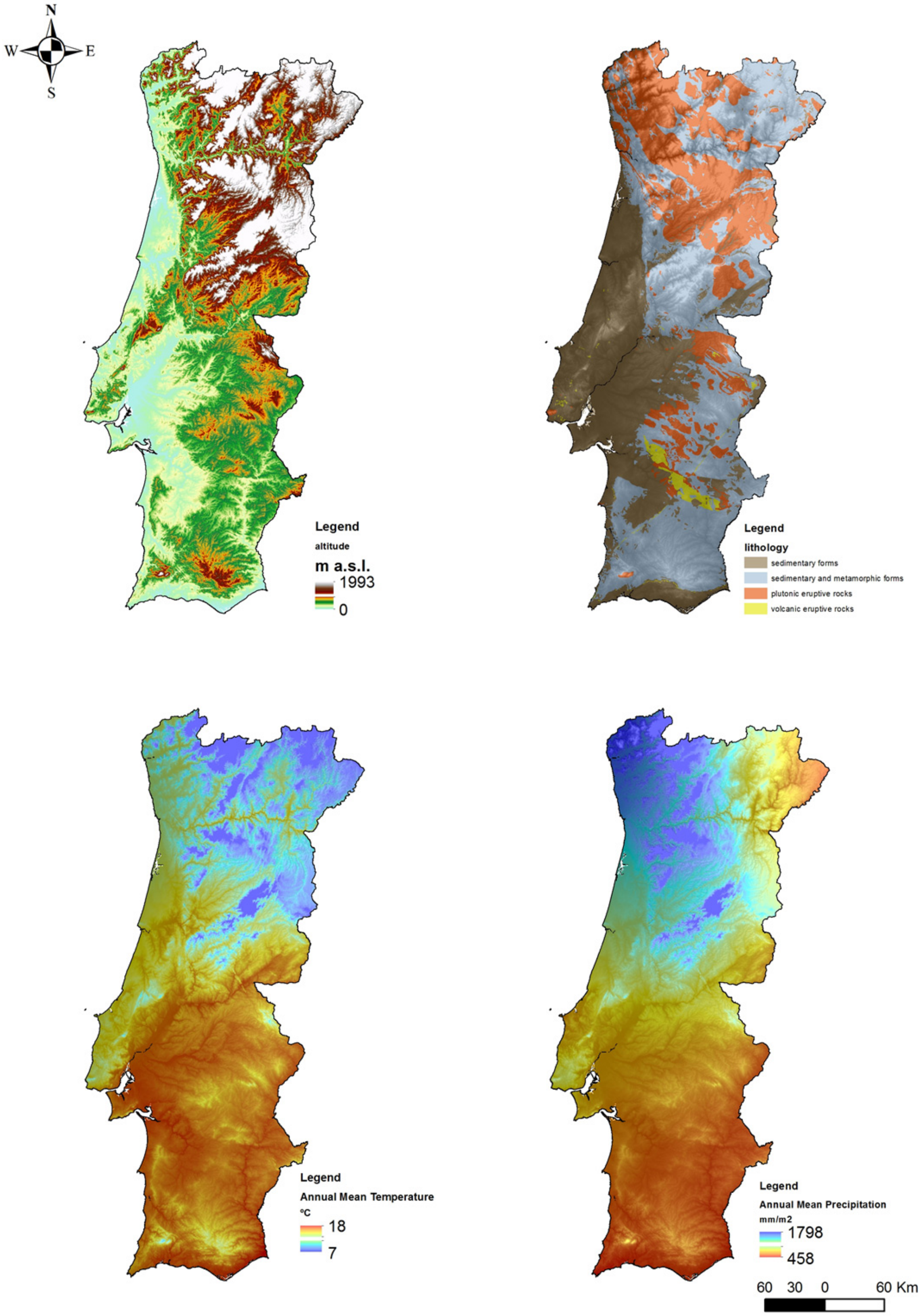


Figure 2.3 Main abiotic conditions in mainland Portugal: (top left) Digital elevation model; (top right) Simplified geological map (main bedrock types); (bottom left) Mean annual temperature; (bottom right) Mean total annual precipitation. Sources: (top left) SRTM (2006), (top right) Atlas do Ambiente Digital, DGA-MAOT (2000), (bottom left and right) Worldclim (2005).

2.1.1.2. Human occupation and land uses

The total population is roughly 10 million inhabitants, clearly concentrated in the north and centre coastal areas (INE, 2010) (Figure 2.4, left). Socio-economic and demographic trends that have prevailed in rural areas of Portugal during at least the last four decades have contributed to high landscape level susceptibility to fire. Rural areas have experienced a substantial population decrease (and aging; Figure 2.4, right) during the second half of the 20th century, leading to the abandonment of agricultural lands, to the decrease in the size of herds, and to the reduction in the consumption of forest fuels by animal grazing and by fuel wood harvesting (Rego, 1992). Areas of marginally productive agriculture were converted to forest plantations or abandoned to the natural process of ecological succession, and thus gradually converted to scrubland and woodland, as in other regions of southern Europe (Lloret *et al.*, 2002; Mouillot *et al.*, 2003).

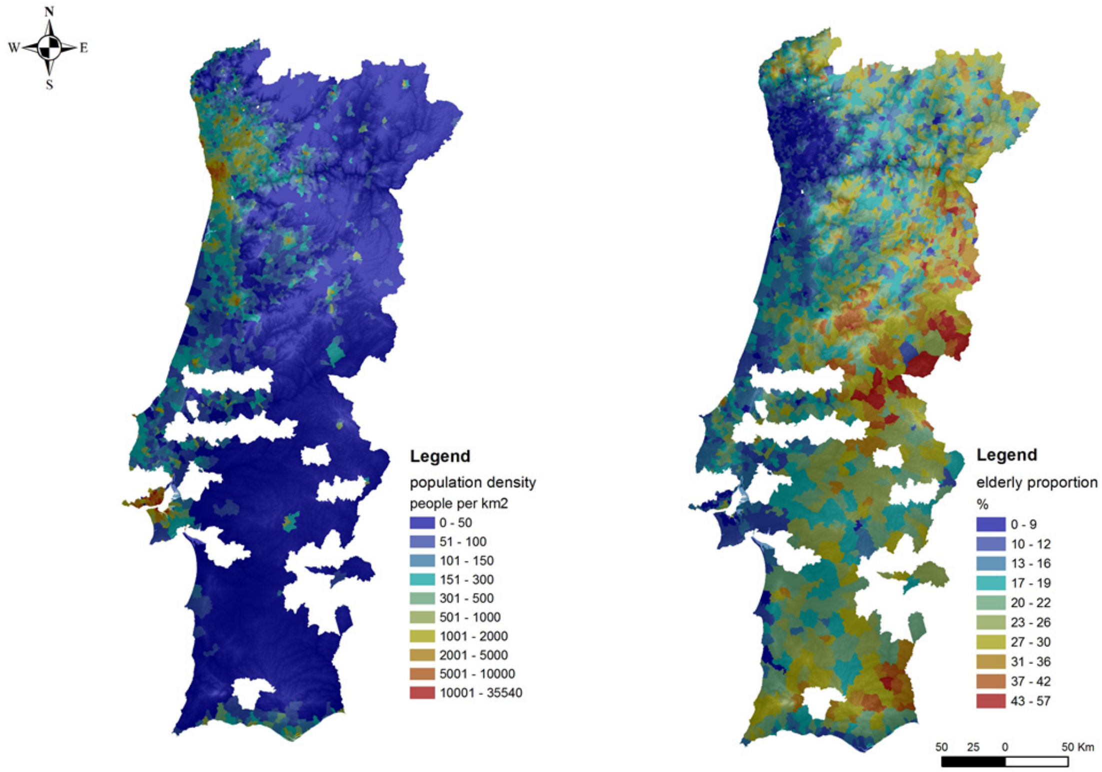


Figure 2.4 Selected demographic features of mainland Portugal: (left) Demographic density; (right) Elderly proportion by civil parish. Sources: INE (2010).

Nonetheless, agricultural and grazing areas still represent a large portion of the country (Figure 2.5). Present throughout the entire territory, they spread over larger areas in the southern and central parts of the country. In northern and central Portugal, land ownership is typically very fragmented and the agricultural landscape is a fine-grained mosaic of small parcels of diverse crops, vineyards, and olive groves. The agricultural landscapes of southern Portugal are more extensive and homogeneous, dominated by dry-land farming of cereal crops and agro-forestry systems ("montado"). Production forestry (mainly of eucalypt, pine and evergreen oaks) and urban occupation are other key land uses in mainland Portugal.

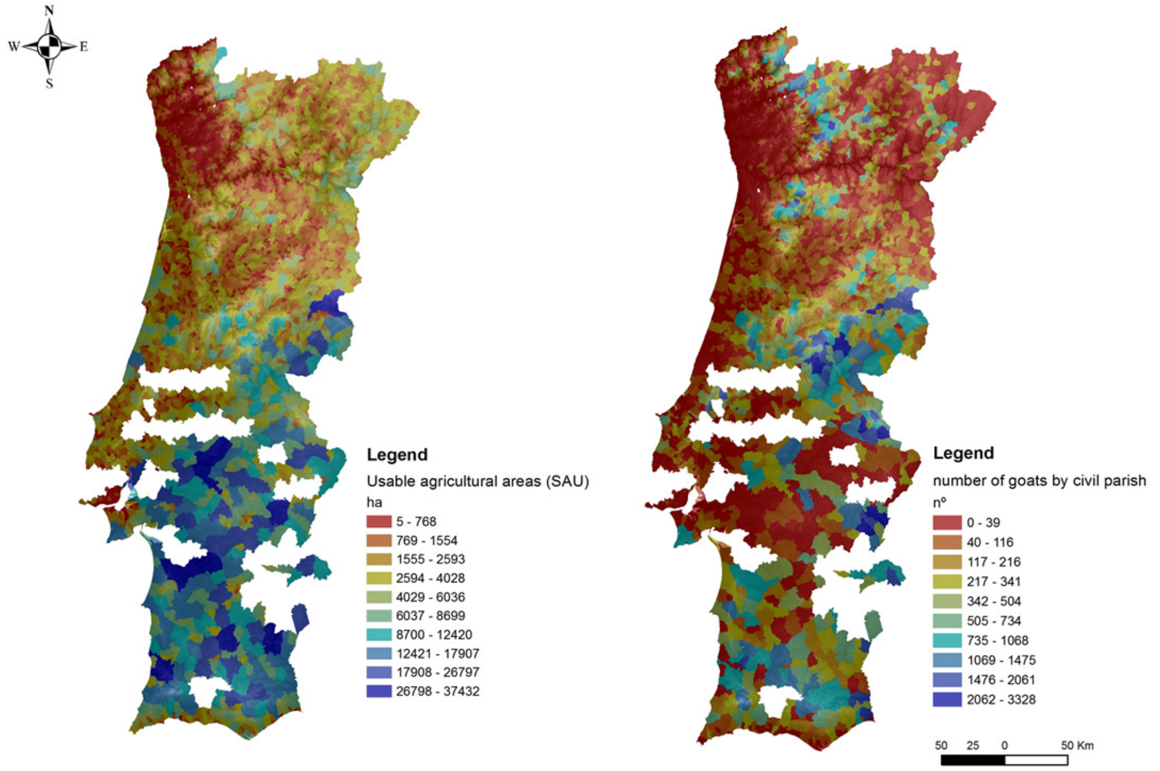


Figure 2.5 Selected agricultural features of mainland Portugal: (left) Usable agricultural areas (UUA, or SAU) per civil parish; (b) Number of goats per civil parish, an indicator of grazing pressure. Sources: INE (2010).

2.1.1.3. Vegetation and land cover

Potential natural vegetation in mainland Portugal is primarily driven by climate gradients related to latitude, longitude and altitude (Figure 2.6, left). As a general pattern, in the north-western Atlantic areas and at high elevations further south, *Quercus robur* and *Betula celtiberica* are the dominant tree species in natural woodlands. *Quercus pyrenaica* predominates in mountains and high plateaux with rainy Mediterranean climate, *Quercus faginea* ssp. *broteroi* is potentially widespread in the centre-western lowlands, and the evergreen *Quercus suber* and *Quercus rotundifolia* predominate under dry Mediterranean climates in the southern half of the country and in the upper Douro valleys (Costa *et al.*, 1998; Capelo *et al.*, 2007).

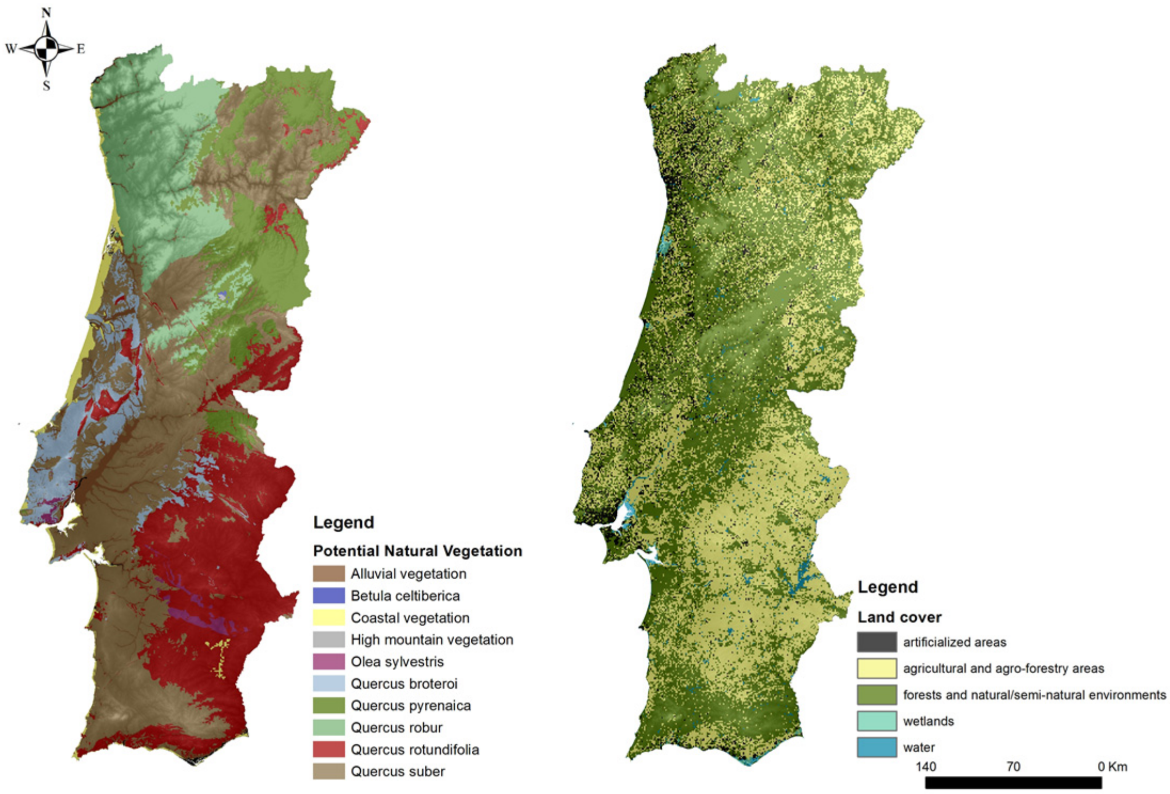


Figure 2.6 Vegetation and land cover in mainland Portugal: (left) Simplified map of potential natural vegetation; (right) Simplified land cover map (broad categories). Sources: (left) Capelo *et al.* (2007), (right) IGEOE (2010).

In terms of land cover (Figure 2.6, right), a large portion of the country is occupied by agricultural areas (ca. 20%), forests (ca. 20%) and scrublands (ca. 25%) (IGP, 2010). In forest and scrubland areas, where most rural fires occur (Pereira, 2006), eucalypt (*Eucalyptus globulus*) plantations are abundant all along the western half of Portugal and in a few more interior areas in the central and southern parts of the study area. Maritime-pine (*Pinus pinaster*) stands are located mainly in the northern half of the country.

Deciduous oak woodlands of *Quercur robur* and/or *Q. pyrenaica* are common in mountain and high plateau areas. Evergreen oak woodlands predominate in the southern half of Portugal, with Cork-oak (*Quercus suber*) mainly in south-western Portugal, in the north-eastern lowlands and along the Tagus river valley, and Holm-oak (*Quercus rotundifolia*) predominating in the south-east. Shrub understories are common in all of these forest and woodland types. In pine and eucalypt stands, the main understory shrubs are gorse (*Ulex* spp.) and heath (*Erica* spp. and *Calluna vulgaris*). *Cistus* spp. dominate the understory layer in open evergreen oak woodlands (DGF, 2001).

Scrublands are common throughout most of the country, particularly in mountainous regions (Figure 2.6, right). The more widespread scrub formations in Portugal are dominated by families *Fabaceae* (*Cytisus*, *Genista*, *Pterospartum*, *Ulex*), *Ericaceae* (*Arbutus*, *Calluna*, *Erica*) and *Cistaceae* (*Cistus*, *Halimium*). As a general pattern, *Cytisus* species (brooms) predominate in areas with deep soils derived from granitic bedrock, while *Cistus* species predominate on shallow soils derived from schist or granite. Broom species also dominate old-field successions and post-fire succession in areas formerly occupied by deciduous woodlands or pine stands.

In the northern third of Portugal and at high elevations, heath and gorse scrublands are the most common. In the southern half of Portugal, especially in the southeast, there are large areas of *Cistus ladanifer* scrub. Limestone areas are typically covered by a *Quercus coccifera* garrigue. In very restricted areas, maquis-type formations of tall scrublands can be found, mainly composed of *Arbutus unedo*, *Olea europaea*, and arborescent *Quercus coccifera* (Pena and Cabral, 1996).

2.1.2. Regional level: Northern Portugal

2.1.2.1. Location and abiotic conditions

For analyses of post-fire vegetation recovery at the regional scale, the North of Portugal was chosen as test area since it is among those with the highest incidence of wildfires across Europe (Figure 2.7).

The studied area comprises the northern part of continental Portugal, which includes the westernmost transition between the Atlantic and Mediterranean environmental zones and biogeographic regions of Europe (Costa *et al.*, 1998; Metzger *et al.*, 2005). This area is characterized by wide variations in elevation, ranging from 0 to 1993m, thus resulting in a large heterogeneity of environmental conditions, namely in terms of climate and soils. The Douro river drainage basin occupies around 50% of the region.

Bioclimatically, most of this territory is Mesomediterranean and Supramediterranean (Rivas-Martínez *et al.*, 2002). The average annual precipitation varies between ca. 400mm in the eastern lowlands and over 2800mm in the north-western mountains. Mean annual temperature varies between 7.5 ◦C and 16◦C; the average maximum is around 22–32◦C; the average minimum is around 0–8◦C (IPMA, 2012).

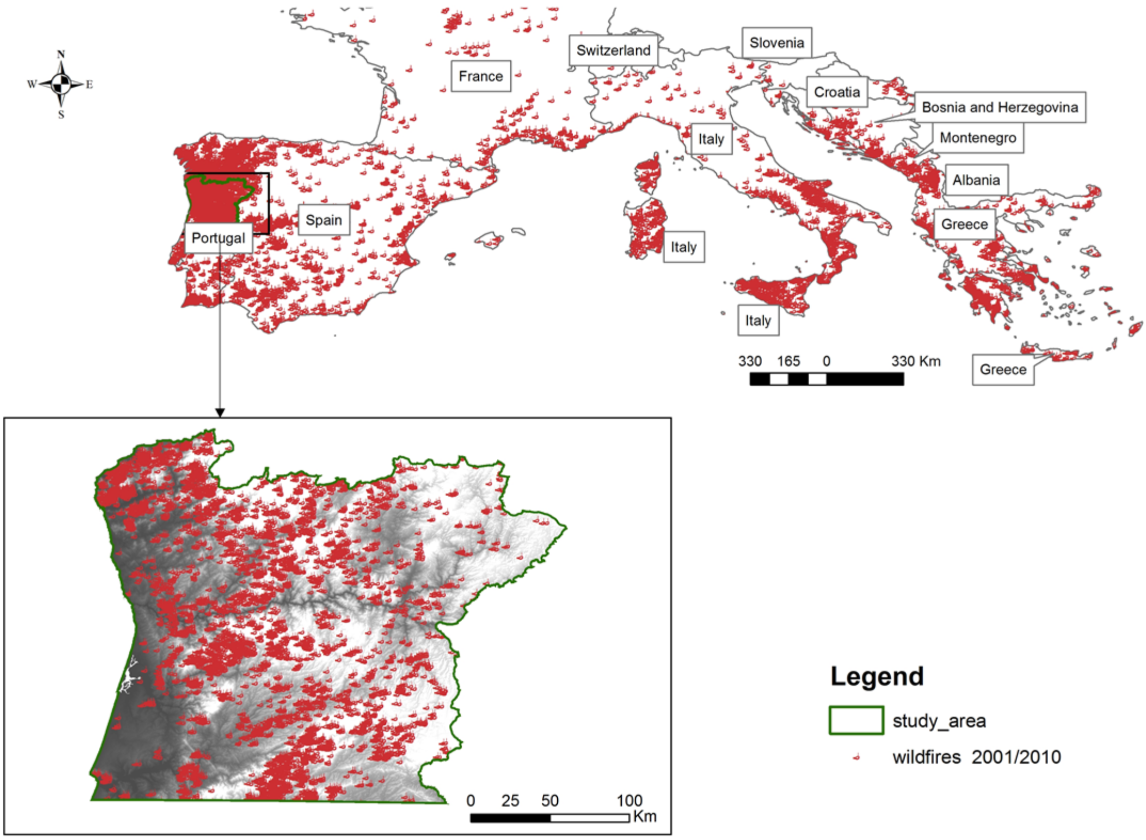


Figure 2.7 Wildfires in Southern Europe for the time frame 2001-2010; the study area is located in the highest fire incidence region (Northwest Iberian Peninsula). Sources: EFFIS.

As described above, this study area has the highest frequency of wildfires in Portugal (Pereira *et al.*, 2006). This region also shows a strong climatic transition, where the Atlantic influence meets the Mediterranean, leading to a strong spatial gradient of temperature and precipitation. This gradient, together with the rough, mountainous physiography, produces a heterogeneous landscape suitable for testing the existence of regional variations in patterns of fire selection and post-fire regeneration.

2.1.2.2. Human occupation and land uses

The region has a resident population of ca. 3.2 million people and a relatively high population density, particularly towards the west (Figure 2.8, left). Agriculture and forestry are the dominant land uses, with various proportions of the active population dedicated to the primary sector (Figure 2.8, right).

In recent decades, the socioeconomic and demographic evolution of marginal rural areas led to widespread land abandonment and subsequent scrub encroachment, as well as the afforestation of former agricultural land. In both cases, a higher accumulation of fuels was generated, leading to a higher risk of fire (Silva, 1990; Rego, 1992; Moreira *et al.*, 2001, 2009).

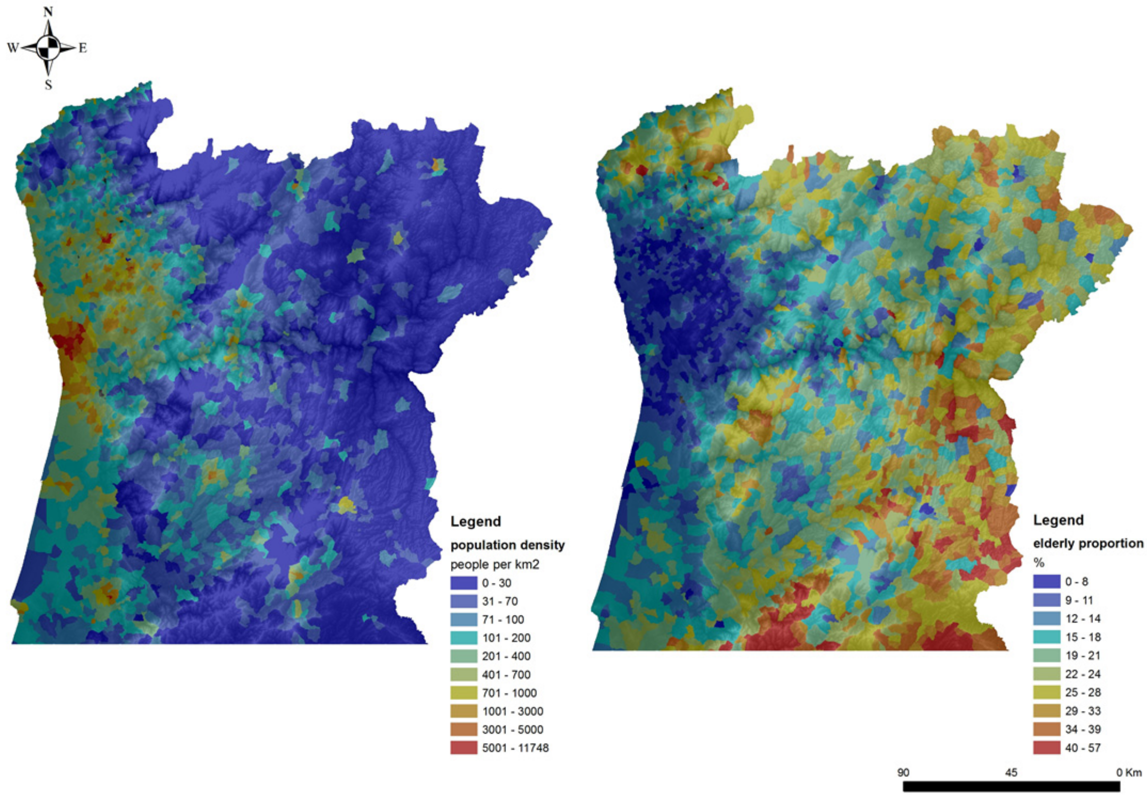


Figure 2.8 Selected socioeconomic features of Northern Portugal: (left) Population density; (right) Elderly proportion; data aggregated at the civil parish level. Sources: INE (2010).

2.1.2.3. Vegetation and land cover

Native forests are dominated by deciduous broadleaved trees in Atlantic areas of the northwest and by evergreen sclerophyllous trees in Mediterranean areas towards northeast (Figure 2.9, left). Biogeographically, the region is divided in two parts: the Eurosiberian region, in the north-west half, with *Quercus robur*, *Pyrus cordata* or *Ilex aquifolium* as indicator species; and the Mediterranean region, in the north-eastern part, with *Quercus faginea* ssp. *faginea, Quercus pyrenaica, Quercus suber and Quercus ilex* as representative species (Costa *et al.*, 1998; Capelo *et al.*, 2007). *Quercus suber* and *Quercus faginea* ssp. *broteroi* predominate in the centre-western areas (Figure 2.9, left). Evergreen plantations of eucalypts and pines, together with a high diversity of agricultural land and urban areas (Figure 2.9, right), further contribute to enhance landscape ecological heterogeneity.

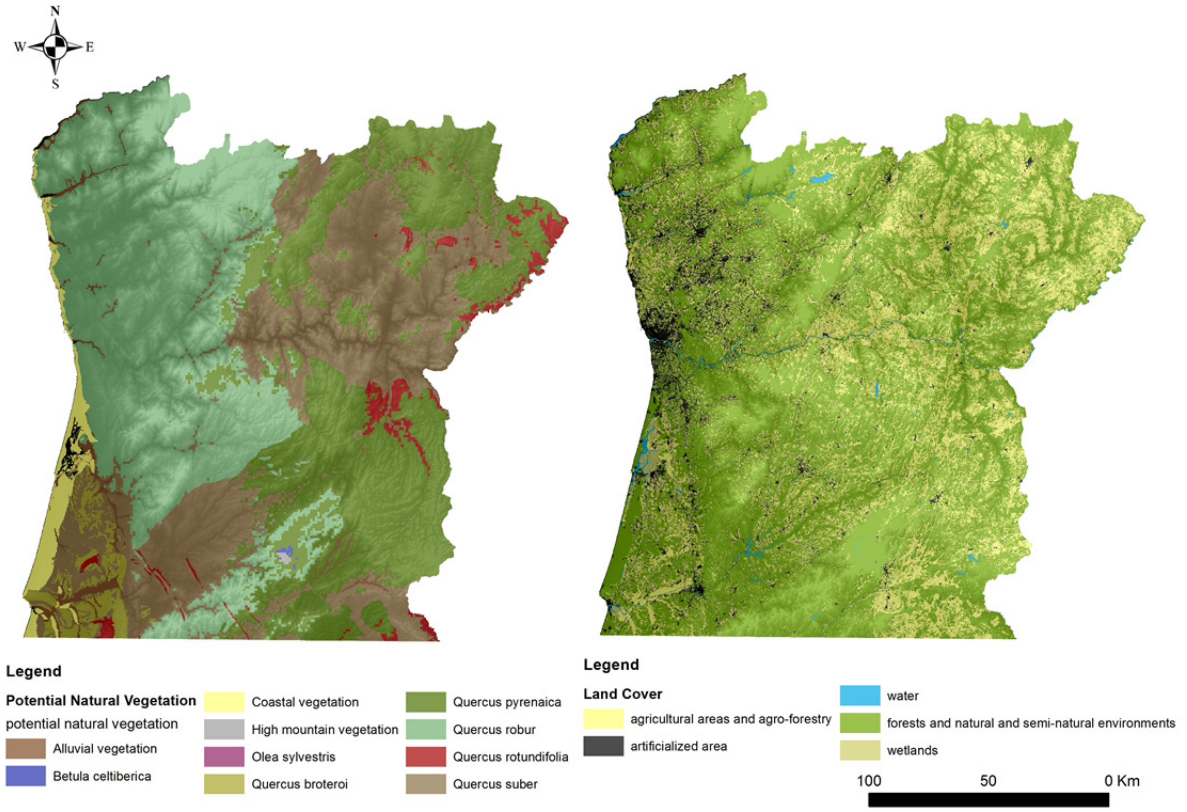


Figure 2.9 Vegetation and land cover in Northern Portugal: (left) Simplified map of potential natural vegetation; (right) Simplified map of main land cover types. Sources: (left) Capelo *et al.* (2007), (right) IGP (2010).

2.1.3. Sub-region level: Alto Minho

2.1.3.1. Location and abiotic conditions

The Alto Minho region is located in the northwest corner of Portugal and includes the most Atlantic (Eurosiberian) territories in the country. Terrain morphology in this small region is quite complex. With ca. 50 km of sandy and rocky beaches along the western coastline, elevation rapidly raises to above 1500m in the highest peaks of the Serra do Gerês (Figure 2.10), which hold national records for total annual precipitation (ca. 3000 mm/m^2).

Three major river valleys (Minho, Lima, and Cávado) cross the region and represent, together with the coastline, the climatically more benign areas in the region. As usual, temperature and precipitation follow inverse patterns (Figure 2.11), with highlands recording the lowest temperatures and the highest precipitations, whereas in the river valleys and along the coast temperatures are higher and rainfall values are lower. The range of mean temperatures corresponds to ca. 10º C to 15º C, and mean annual precipitation varies from 1200 mm/m^2 in lowlands to well over 2000 mm/m^2 in the eastern mountain tops.

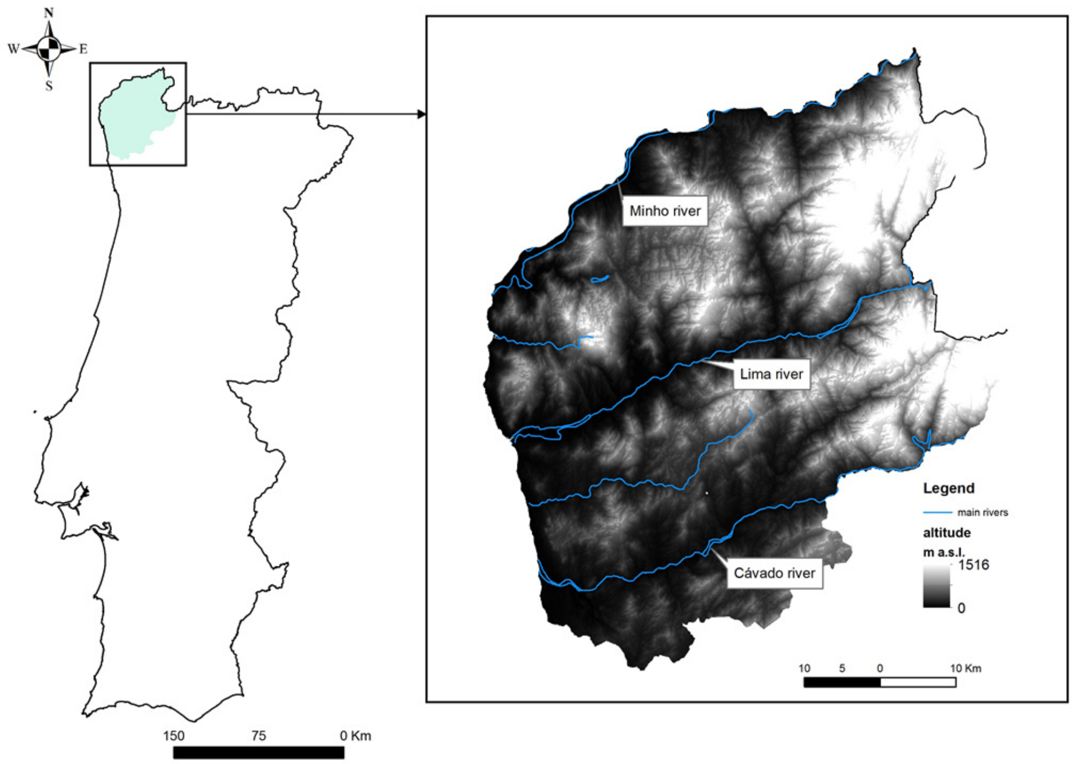


Figure 2.10 (left) Location of the Alto Minho region in Portugal; (right) Digital elevation model and main rivers.

2.1.3.2. Human occupation and land uses

The resident population (ca. 500 000 people) is unequally distributed across the study area, with the vast majority living in the coastal areas and in the southern river basin (Cávado), whereas the highlands and the most interior areas are poorly populated (Figure 2.12, left). Recent demographic evolution has been strengthening this tendency (Figure 2.12, right).

With a relatively low industrial development, the vast majority of the land is used for agriculture and forestry. The small property regime is the rule, with a small increase in property size in the more mechanized agricultural lands of the Cávado basin. Most of the lowland agricultural areas are dedicated to the production of maize and other dairy farming related cultures. In the highest elevations, cattle and herd grazing on meadows and pasturelands are common land uses.

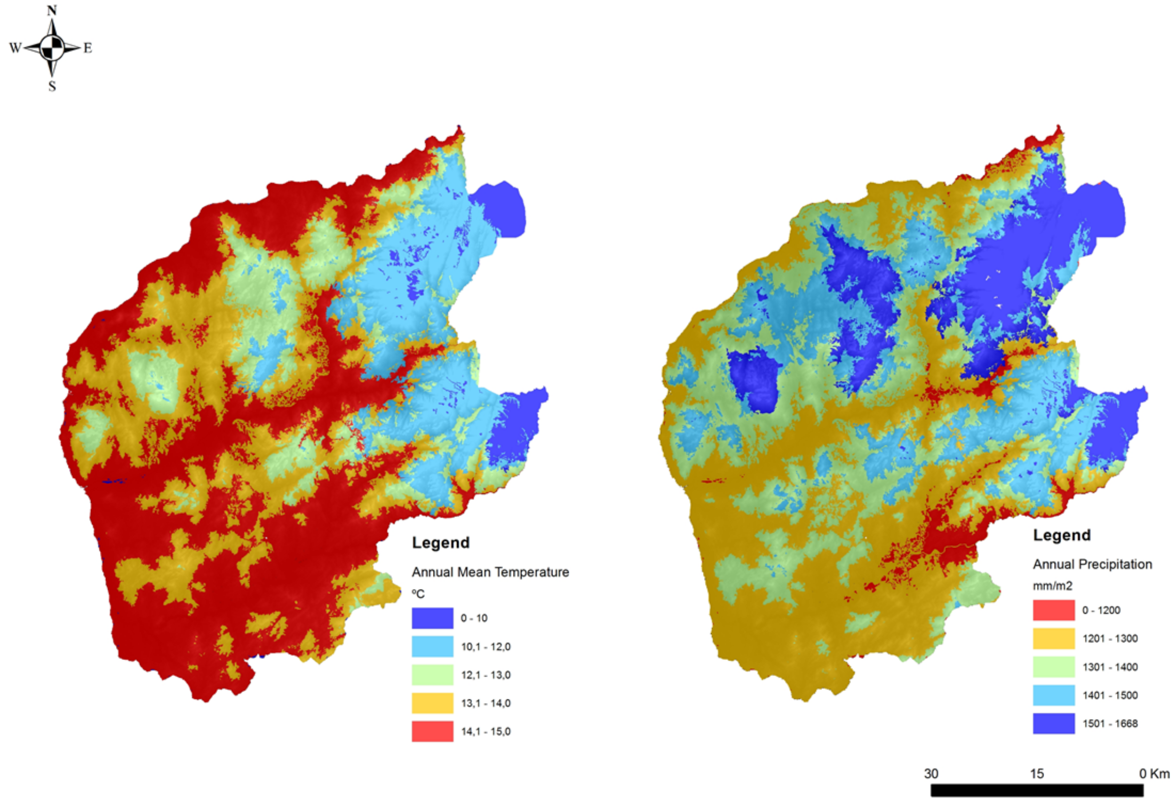


Figure 2.11 Climatic conditions in the Alto Minho region: (left) Mean annual temperature; (right) Mean total annual precipitation (b). Sources: Worldclim (2005).

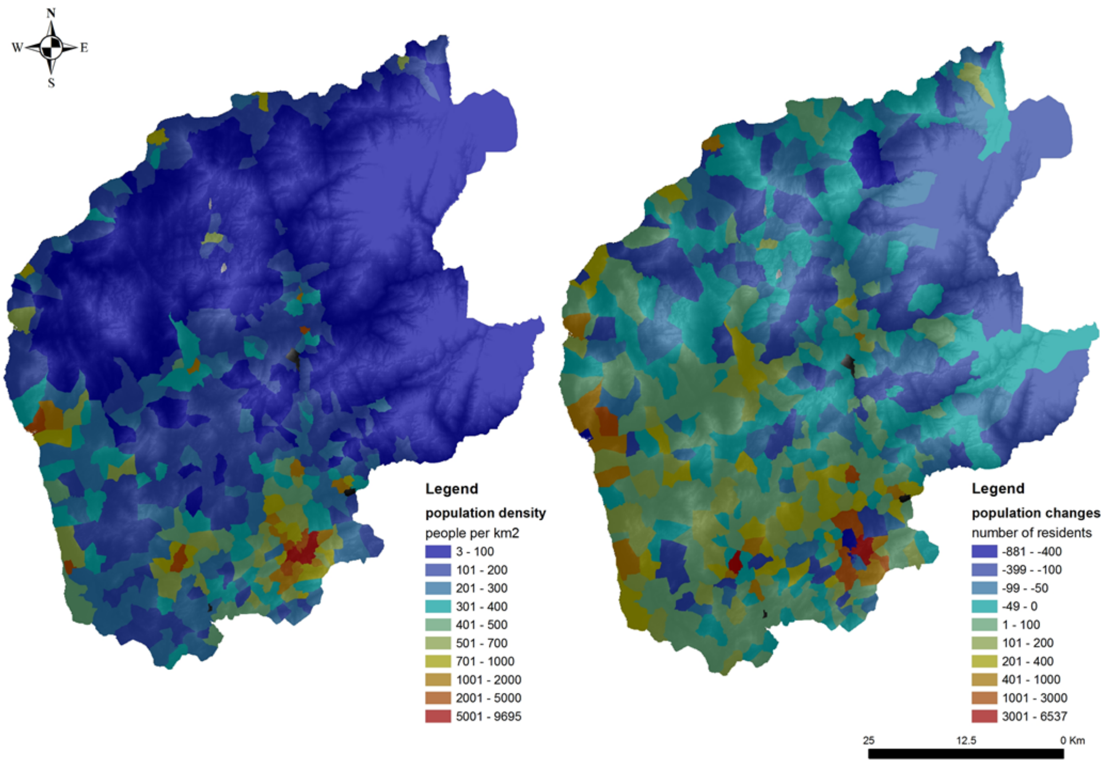


Figure 2.12 Selected socioeconomic features of the Alto Minho region (data aggregated at the civil parish level): (left) Population density; (right) Recent population changes (1990-2001). Sources: INE (2010).

2.1.3.3. Vegetation and land cover

The Alto Minho region is a fine-grained mosaic in which land parcels are traditionally well defined and utilized in different ways for agriculture, forestry and pastoralism. Biogeographically the region is located at the southwest end of the Eurosiberian region, with *Quercus robur* and *Betula celtiberica* as the dominant native tree species (Costa *et al.*, 1998). In spite of its small size, the study area comprises a noteworthy diversity of potential vegetation types, evidencing its variations in altitude, climate, topography and lithology (Figure 2.13, left).

The land cover types related to forests and scrublands occupy ca. 60% of the study area, with agriculture occupying ca. 28% (Figure 2.13, right). The large amount of available biomass and the high productivity rates are important reasons to place this region among those with the highest fire frequencies in Europe, although the average size of the burned areas is small (European Commission, 1996; Moreno *et al.*, 1998).

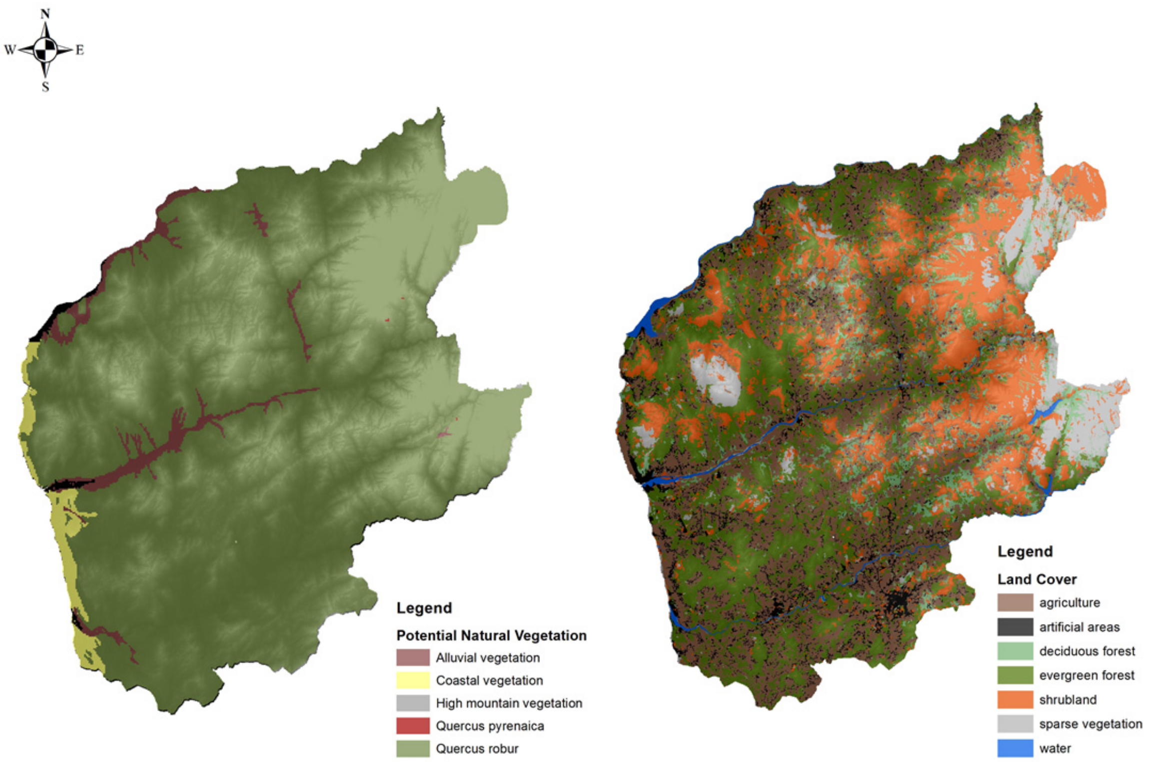


Figure 2.13 Vegetation and land cover in the Alto Minho: (left) Simplified map of potential natural vegetation; (right) Broad land cover types in year 2000. Sources: (left) Capelo *et al.* (2007), (right) Vicente *et al.* (2011).

2.1.4. Municipality level: Baixo Tâmega

2.1.4.1. Location and abiotic conditions

The Baixo Tâmega study area is located in the northwest of Portugal (Figure Figure 2.14, left), at the eastern end of the Porto district, in the NUTS-II "North" (NUTS-III "Tâmega"). It comprehends territories belonging to three municipalities (Amarante, Baião, and Marco de Canaveses), with a total area of ca. 678 km^2. The eastern part of the area is under protection as part of the Natura 2000 network (Site of Community Importance "Alvão-Marão", PTCON0003) and is also included in an Important Bird Area (IBA PT049). Moreover, in recent years the three municipalities have been engaged in the formal classification of the Aboboreira and Marão mountains as a regional protected area (Honrado and Vieira, 2009).

There are two main mountain areas that delineate the physiography of the region: the Serra do Marão (1314m of maximum elevation), at the northeastern end, and the Serra da Aboboreira, a smaller massif that is completely included in the study area (Figure 2.14, right). The climate is temperate Atlantic and humid, with a short dry season in summer giving it a sub-Mediterranean character, particularly along the Douro and Tâmega river valleys.

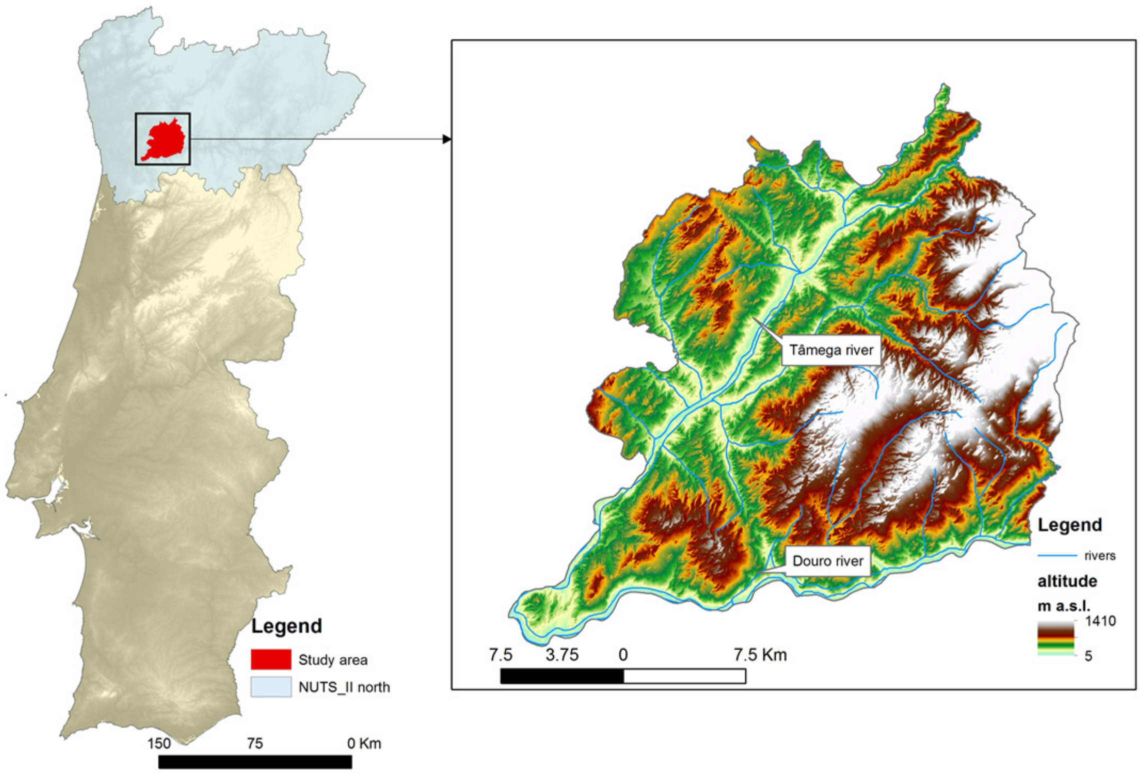


Figure 2.14 (left) Geographic location of the Baixo Tâmega study area in continental Portugal; (right) Elevation map with main rivers. Sources: (left) APA (2010), (right) SRTM (2004).

Geologically, the area is clearly dominated by several types of granite, with schist occupying the eastern and northern ends (Figure 2.15, left). Soils are predominantly regosoils and antrosoils on granite, where mild slopes and agro-pastoral activities are/were common, and leptosoils and regosoils on schist, where the steep slopes hamper agriculture but allow forestry and extensive grazing by sheep and particularly by goats (Figure 2.15, right).

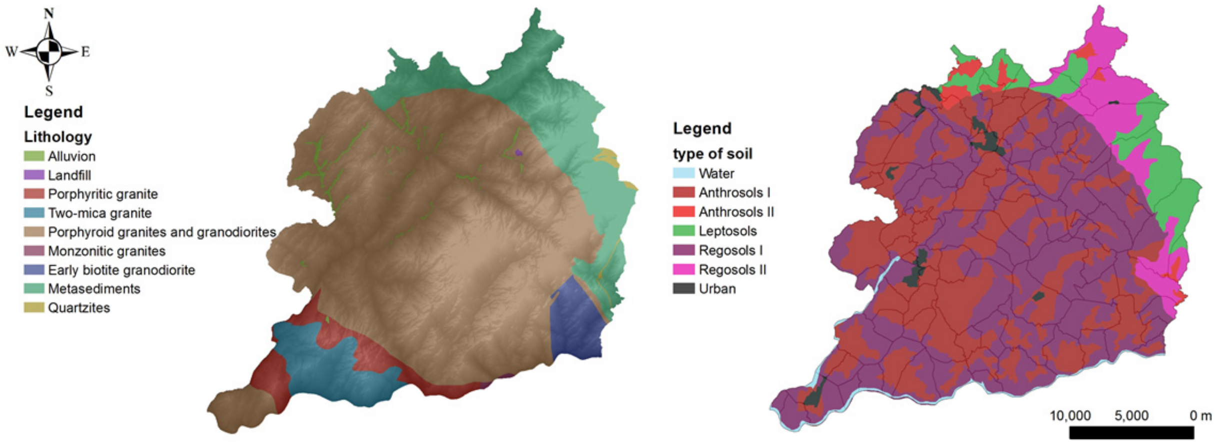


Figure 2.15 Abiotic conditions in the Baixo Tâmega study area: (left) Bedrock types; (right) Soil types. Sources: Honrado and Vieira (2009).

2.1.4.2. Human occupation and land uses

Human occupation is heterogeneous in the region, with stronger urban development along the Tâmega valley (including the towns of Amarante and Marco de Canaveses) contrasting with scattered rural villages in the more mountainous areas (Figure 2.16, left). Roughly one third of the civil parishes have more than one third of their resident population in the primary sector, which testifies the rural character of most of the area (Figure 2.16, right). Agriculture, forestry and localized urban development are thus the main land uses in this study area (Honrado and Vieira, 2009). In the Douro and Tâmega valleys, several hydroelectric dams have also contributed to shape the landscapes that can be observed today.

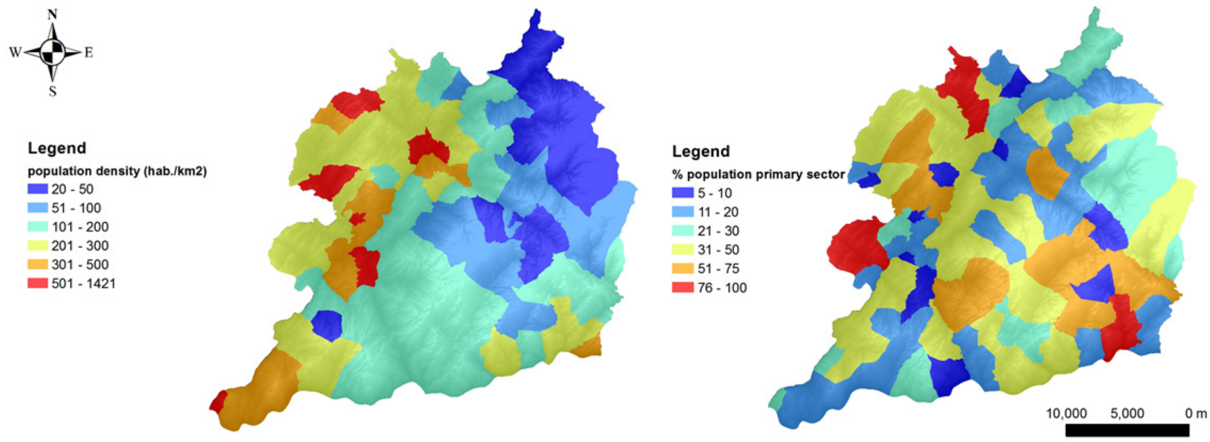


Figure 2.16 Selected socioeconomic features of the Baixo Tâmega study area, aggregated at the civil parish level: (left) Population density; (right) Percentage of population in the primary sector. Sources: Honrado and Vieira (2009).

2.1.4.3. Vegetation and land cover

Natural potential vegetation in the Baixo Tâmega region would correspond entirely to deciduous oak woodlands of *Quercus robur*. *Quercus pyrenaica* and *Betula celtiberica* in mountains, and *Quercus suber* in lowlands, would be other common native tree species (Honrado and Vieira, 2009). Oak woodland and scrubland are today common in marginal areas due to abandonment of farming and grazing, but heath and broom scrubs are by far the most common natural vegetation types in the area.

Agricultural areas, several types of forests, and scrub are the dominant types of land cover (Figure 2.17). Fine grained landscape mosaics of cropland, urban and forest areas are the rule in lowlands, whereas mountain and high plateau areas are dominated by low and tall scrub with various presence of forest. Recent land cover change has involved urban expansion as well as the loss of forest areas and the development of continuous areas of scrub and degraded land (Figure 2.17), mostly driven by rural abandonment and wildfires.

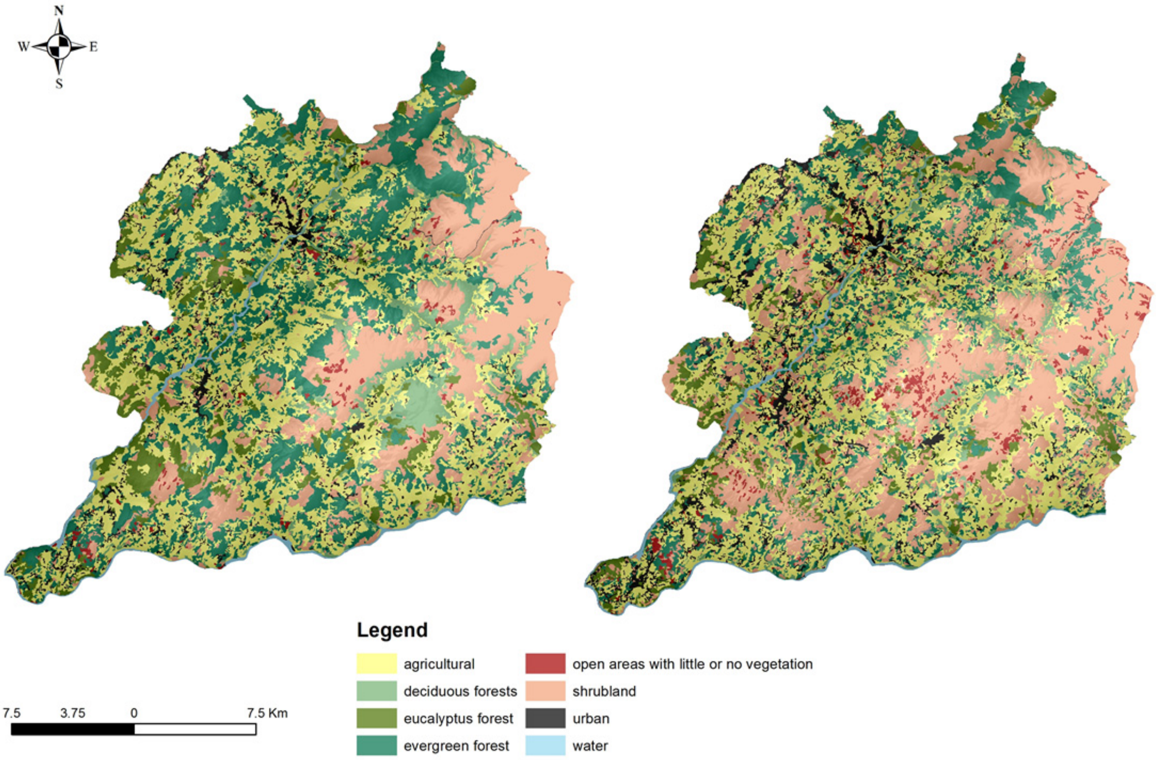


Figure 2.17 Recent land cover changes in the Baixo Tâmega municipalities: (left) Simplified land cover map for year 1990; (right) Simplified land cover map for year 2000. Sources: Honrado and Vieira (2009, adapted).

2.2. Databases and data processing

The selection and processing of variables extracted from the several databases was done for a wide range of factors capable of influencing fire history or post-fire resilience and thus potentially helpful in their interpretation. Those variables and datasets were selected based on extensive literature review and expert judgment, as well as their availability for each of the study areas under analysis. All variables were computed and managed in a Geographic Information System (GIS) and transformed when necessary, following the procedures described below.

2.2.1. Wildfire data

In recent decades, Portugal has developed sizable efforts in the cartography of burnt areas (Figure 2.18).

Portuguese fire statistics are available from the national forest authority (ICNF, formerly AFN) in the form of polygons with a minimum mapping area of 5 hectares, for the time period of 1990–2010 (http://www.afn.min-agricultura.pt/portal/dudf/cartografia/info-geo). These data were computed by semi-automated processing of Landsat 5 Thematic Mapper satellite images (Pereira and Santos, 2003; Moreira *et al.*, 2009).

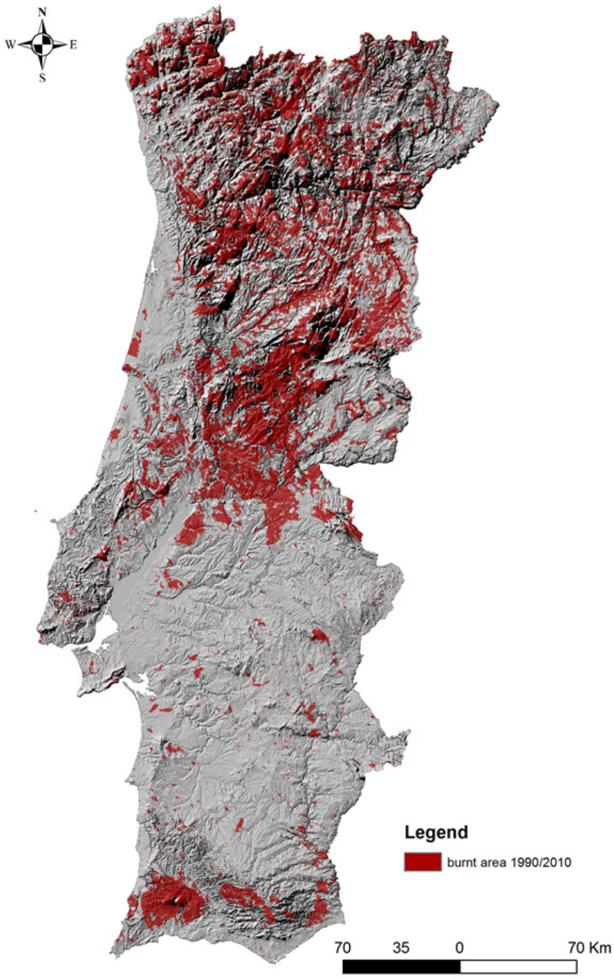


Figure 2.18 Polygons of burnt areas (minimum mapping area: 5 hectares), for the time period 1990–2010, available from the National forest authority (ICNF, formerly AFN).

This database was used in all studies throughout this thesis (Figure 2.19):

- at the national level, the official map of civil parishes and zonal statistics were used to calculate the proportion of burnt area in the 1990-2000 time frame for each parish, used as a response variable in wildfire modelling;
- for the Northern Portugal study area, the fire dataset was used to produce a polygon cartography of the areas that, in the 2000-2010 time frame, were only burnt in year 2005, to assess post-fire recovery;
- for the Alto Minho study area, the polygons from the 1991-2000 and 2001-2010 time frames were used, respectively, in the training and testing of a rule set to explain the occurrence of fires; and
- for the Baixo Tâmega study area, fire data from the 1990-2007 time frame were used to produce a local stratification for sampling design (selection of field sites).

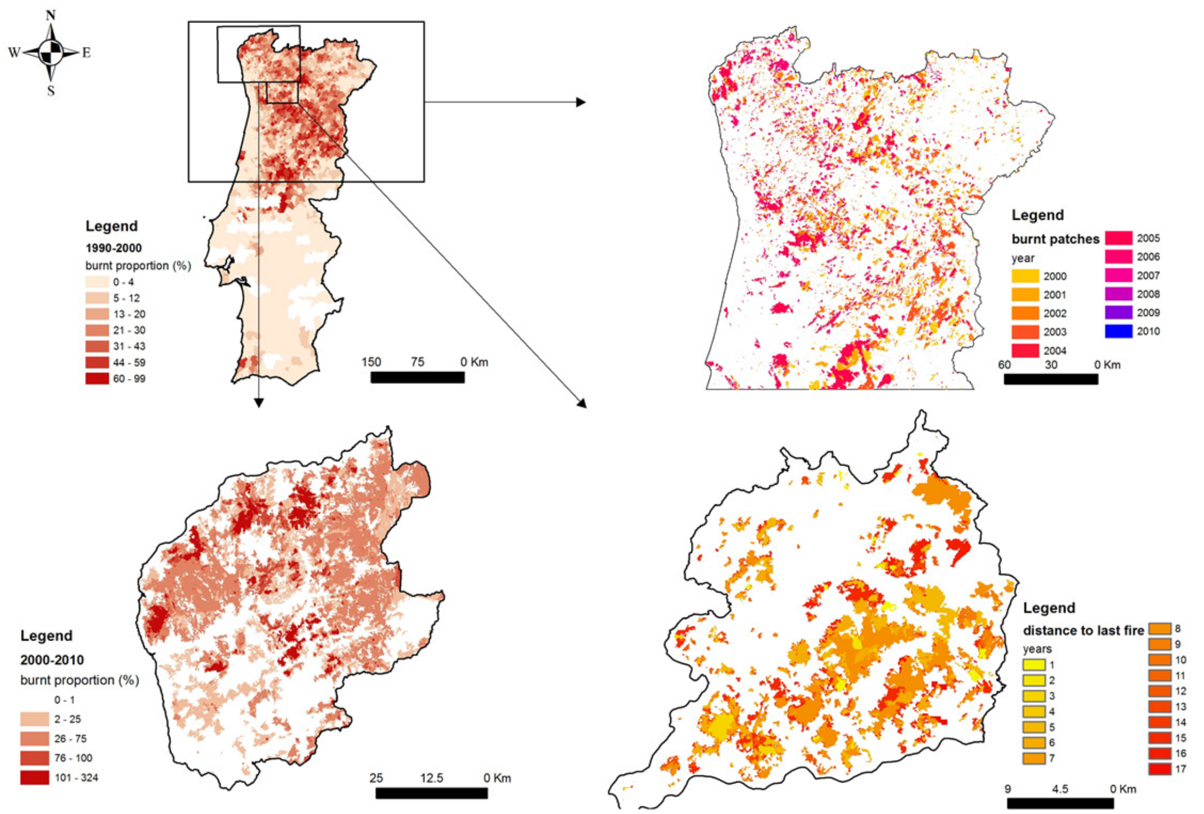


Figure 2.19 Applications of the national wildfire database in the four study areas: (top left) Continental Portugal (burnt proportion in 1990-2000); (top right) Northern Portugal (burnt patches in 2000-2010); (bottom left) Alto Minho (burnt proportion in 2000-2010); (bottom right) Baixo Tâmega (time distance to last recorded fire).

2.2.2. National level: Continental Portugal

In the analysis of wildfire patterns in Portugal, 80 potentially explanatory variables were computed and organized into four categories: climatic, landscape, topographic, and human factors. Since part of the data were only available at the civil parish level, all the information was pre-processed in a Geographic Information System (GIS) and aggregated values were obtained for each civil parish (see below).

2.2.2.1. Climatic variables

Climatic conditions are known to affect fuel accumulation and moisture (e.g. Syphard *et al.*, 2008; Vilar *et al.*, 2010), thus having an effect on the probability of a fire to occur as well as on its spread over the landscape. Considering the temporal scale of our study, we used climatic variables derived from averages of weather conditions over several decades, obtained from Worldclim (Hijmans *et al.*, 2005; Table 2.1).

Table 2.1 Climatic variables used in the analysis of national fire patterns: name, description, variable group, and data source.

Variable name	Variable description	Variable group	Data source
Bio1	Annual Mean Temperature	Climatic	WORLDCLIM (Hijmans *et al.*, 2005)
Bio2	Mean Diurnal Range (Mean of monthly (max temp - min temp))		
Bio3	Isothermality (BIO2/BIO7) (* 100)		
Bio4	Temperature Seasonality (standard deviation *100)		
Bio5	Max Temperature of Warmest Month		
Bio6	Min Temperature of Coldest Month		
Bio7	Temperature Annual Range (BIO5-BIO6)		
Bio8	Mean Temperature of Wettest Quarter		
Bio9	Mean Temperature of Driest Quarter		
Bio10	Mean Temperature of Warmest Quarter		
Bio11	Mean Temperature of Coldest Quarter		
Bio12	Annual Precipitation		
Bio13	Precipitation of Wettest Month		
Bio14	Precipitation of Driest Month		
Bio15	Precipitation Seasonality (Coefficient of Variation)		
Bio16	Precipitation of Wettest Quarter		
Bio17	Precipitation of Driest Quarter		
Bio18	Precipitation of Warmest Quarter		
Bio19	Precipitation of Coldest Quarter		

2.2.2.2. Land cover and landscape variables

Land cover, which represents the landscape features of the Earth's surface as a synthesis between environmental conditions and human disturbance (land use), has been extensively associated with fire occurrence (e.g. Syphard *et al.*, 2008; Catry *et al.*, 2009; Martínez *et al.*, 2009; Vilar *et al.*, 2010). For pre-fire land cover, we used the 1:25.000 scale land cover map sheets for 1990 (COS´90) downloadable from the Portuguese Geographic Institute (IGEO, 1990). The land cover sheets were geographically matched with the administrative map using union commands in the ArcGIS software. Detailed land cover categories were combined to produce six broad classes: urban, unproductive, agriculture, water bodies, broadleaved forest, and coniferous forest (see Appendix 1).

We computed composition and configuration landscape metrics, using civil parishes as statistical units (Table 2.2). Composition metrics (percentage of occupation by each broad class) were obtained through GIS analysis in ArcGIS 10 (ESRI, 2011). The following landscape configuration metrics were calculated for each civil parish using the FRAGSTATS software (McGarigal and Marks, 1995): total area, number of patches, patch density, largest patch index, edge density, area-weighted mean patch fractal dimension, patch fractal dimension standard deviation, area-weighted mean patch perimeter-area ratio, perimeter-area ratio standard deviation, interspersion and juxtaposition index, patch cohesion, patch richness, patch richness density, Simpson's evenness index, percentage of like adjacencies, area-weighted mean euclidean nearest neighbour distance, and euclidean nearest neighbour distance standard deviation (Table 2.2). For some of the municipalities, land cover data were not available and for that reason the corresponding civil parishes were excluded from the analyses.

Roads represent improved accessibility to areas where fires can occur. Road density and distance to roads have also been pointed out as important factors in fire occurrence studies (Romero-Calcerrada *et al.*, 2008; Catry *et al.*, 2009; Martínez *et al.*, 2009; Vilar *et al.*, 2010). The data source for the road network was the national road institute (IEP; Matos *et al.*, 2012), from which four variables were computed (Table 2.2).

2.2.2.3. Socioeconomic variables

Human factors (related to demography and socio-economy) are likewise important and have been used in predictive modeling of historical fire patterns (Catry, 2007).

Table 2.2 Landscape variables used in the analysis of national fire patterns: name, description, group, and data source.

Variable name	Variable description	Variable group	Data source
Ta	Total area	Landscape	CNIG 1990. COS´90, Land cover for Continental Portugal
Np	Number of patches		
Pd	Patch density		
Lpi	Largest patch index		
Ed	Edge density		
Frac_am	Area-weighted mean patch fractal dimension		
Frac_sd	Patch fractal dimension standard deviation		
Para_am	Area-weighted mean patch perimeter-area ratio		
Para_sd	Perimeter-area ratio standard deviation		
Iji	Interspersion and juxtaposition index		
Cohesion	Patch cohesion		
Pr	Patch richness		
Prd	Patch richness density		
Siei	Simpson's evenness index		
Pladj	Percentage of like adjacencies		
Enn_am	Area-weighted mean euclidean nearest neighbor distance		
Enn_sd	Euclidean nearest neighbor distance standard deviation		
Eucalipto_AREA_perc	% of land are occupied by *Eucalyptus*		
Flnatural_AREA_perc	% of land are occupied by natural forest		
Matosa_AREA_perc	% of land are occupied by tall scrubs		
Matosb_AREA_perc	% of land are occupied by small scrubs		
Outfolhosas_AREA_perc	% of land are occupied by broadleaved managed forest		
Pinheiro_AREA_perc	% of land are occupied by *Pinus*		
Urbano_AREA_perc	% of land are occupied by urban areas		
Densroadall	Total road density		Instituto das Estradas de Portugal
Densroad6less	Road density (< 6 m wide)		
Densroad6plus	Road density (> 6 m wide)		
Roadareaperc	% of land are occupied by roads		

A simple visual inspection of the national fire database (see Figure 2.18) reveals that in the more densely populated littoral areas the number of ignitions is fairly higher, but due to the reticulated and fragmented character of the landscape fires originated by these ignitions are usually of small dimension. Furthermore, the presence of a large number of settlements, villages and roads allows a faster detection and extinction of fire events. In the specific context of the study area, the causes of fire ignitions have been considered attributable to anthropogenic activities in over 90% of occurrences (Oliveira *et al.*, 2012). Demographic and socioeconomic data were obtained from the statistical national institute (INE 2008) and the Ministry of Agriculture through agricultural census databases (RGA, 1999; Table 2.3).

Table 2.3 Socioeconomic and demographic variables used in the analysis of national fire patterns: name, description, group, and data source.

Variable name	Variable description	Variable group	Data source
Area_06	Agricultural area in use	Socio-economic	RGA, 1999. Recenseamento Geral da Agricultura
Popres91	Resident population in 1991		INE (2008)
Popres01	Resident population in 2001		
Poprestrab91	Resident population in1991		
Poprestrab01	Resident population in 2001		
Popact91	Active population in 1991		
Popact01	Active population in 2001		
Popresqualsec 91	Proportion resident population with secundary education in 1991		
Analf91	Analphabetic proportion in 1991		
Analf01	Analphabetic proportion in 2001		
Proppopres3c 01	Proportion resident population working in agriculture		
Denspop91	Population density in 1991		
Denspop01	Population density in 2001		
Propidosos91	Elderly proportion in 1991		
Propidosos01	Elderly proportion in 2001		
Idepidosos91	Elderly dependency index in 1991		
Idepidosos01	Elderly dependency index in 2001		
Proppoprestra b91	Proportion resident population without any subsidy in 1991		
Proppoprestra b01	Proportion resident population without any subsidy in 2001		
Proppopressu btmp91	Proportion resident population under 18 in 1991		
Proppopressu btmp01	Proportion resident population under 18 in 2001		

Proppoprespe nsref91	Proportion resident population living of welfare in 1991		
Proppoprespe nsref01	Proportion resident population living of welfare in 2001		

Table 2.3 (cont.)

2.2.2.4. Topographic variables

Topographic features affect vegetation distribution, composition and flammability, and have also an influence on local climate variations (Whelan 1995; Syphard *et al.* 2008). Slope may also affect ignitions by limiting accessibility (Widayati *et al.*, 2010). Conedera *et al.* (2011) also found that anthropogenic fires occurred more frequently on gentler slopes.

A set of topographic variables and indices (Table 2.4) was calculated based on the Digital Elevation Model (DEM) available worldwide from the Shuttle Radar Topographic Mission (SRTM, version 4). This DEM is based on SRTM images from NASA, further processed in order to fill in no-data voids existing in the original images (Reuter *et al.*, 2007; Jarvis *et al.*, 2008). Topographic roughness is the amount of land surface variability of a particular area (Stambaugh and Guyette, 2008) and it is a proxy for describing the potential of terrestrial propagation (in this case, fire spread) related to topographic variability. A set of four topographic roughness and terrain complexity indices (mean terrain complexity index, terrain complexity index standard deviation, mean surface and area ratio of a landscape, and surface and area ratio of a landscape standard deviation) were calculated using different ratios between the surface area and the planimetric area, using GIS tools (Table 2.4).

Table 2.4 Topographic variables used in the analysis of national fire patterns: name, description, group, and data source.

Variable name	Variable description	Variable group	Data source
Elev_max	Maximum altitude	Topographic	USGS (2006)
Elev_mean	Mean altitude		
Elev_std	Altitude standard deviation		
Slope_max	Maximum slope		
Slope_mean	Mean slope		
Slope_std	Slope standard deviation		
Tci_mean	Mean terrain complexity index		
Tci_std	Terrain complexity index standard deviation		
Surfratio_MEAN	Mean Surface and Area Ratio of a landscape		
Surfratio_STD	Surface and Area Ratio of a landscape standard deviation		

Figure 2.20 provides four examples of the geographic variations of selected variables from the several groups in continental Portugal.

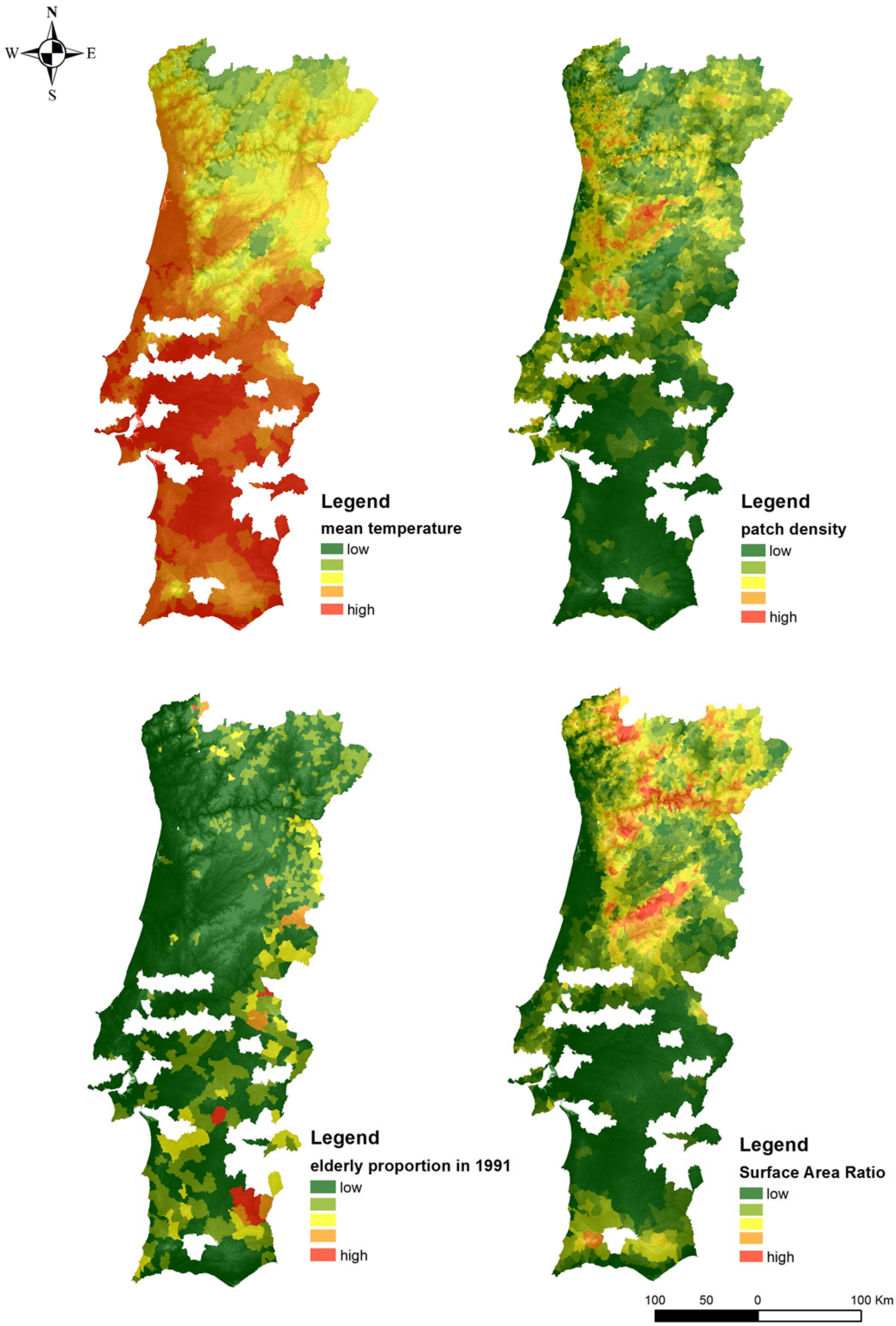


Figure 2.20 Geographic variations of selected variables in continental Portugal, belonging to the Climatic (mean annual temperature; top left), Landscape (patch density; top right), Socioeconomic (age structure; bottom left) and Topographic (surface area ratio; bottom right) groups of variables. Sources: worldclim (top left), IGEOE (top right), INE (bottom left) and srtm (bottom right).

2.2.3. Regional level: North of Portugal

2.2.3.1. The MODIS NDVI time series

In the study of post-fire regeneration in the North of Portugal, in addition to variables obtained from the national fire database (see section 2.2.1) and other national databases on environmental, landscape, socioeconomic and topographic factors (see section 2.2.2), other variables used were derived from the MODIS NDVI time series (Figure 2.21), from which three response variables on post-fire regeneration were computed (see section 2.3.2).

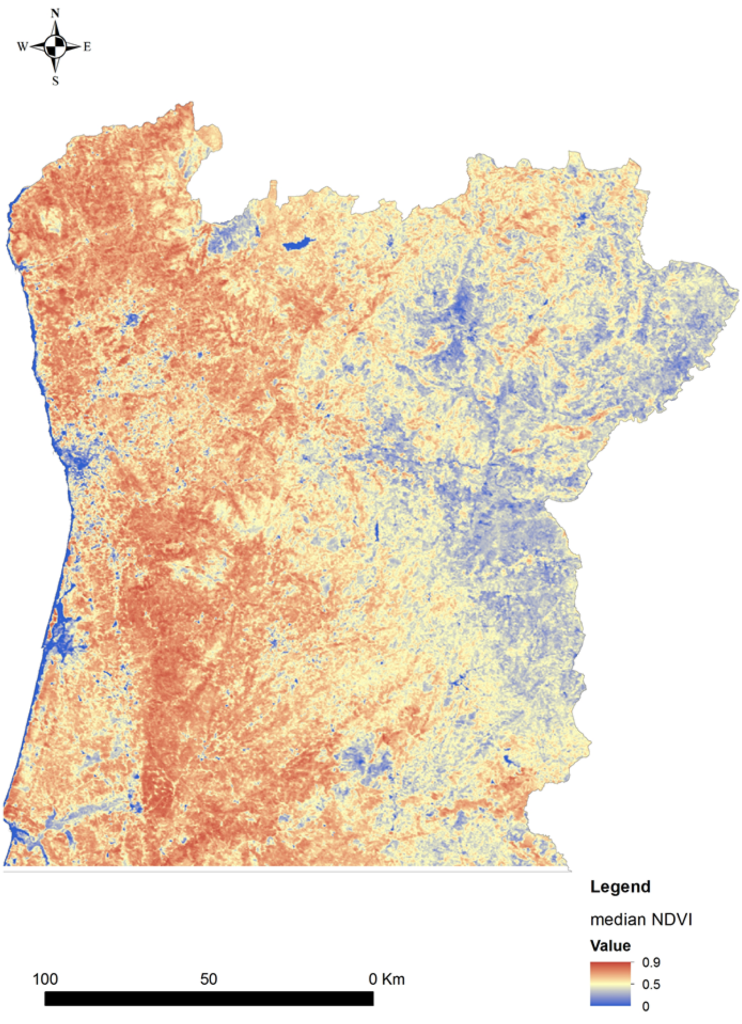


Figure 2.21 Annual median NDVI in the North of Portugal (2001-2010), an example of the variables derived from the MODIS NDVI time series (MOD13Q1).

The 16-day Terra MODIS NDVI product at 250m spatial resolution (MOD13Q1, Collection 5) is based on the Terra MODIS level 2 (L2G) daily surface reflectance product (MOD09 series), which provides red and near-infrared surface reflectance corrected for the effect of atmospheric gases, thin cirrus clouds and aerosols. This product includes a data quality assessment layer (QA binary data) and a pixel reliability layer holding information on overall usefulness and cloud conditions on a per-pixel basis (Solano *et al.*, 2010). We used all 16-day composites between years 2001 and 2010, projected to the WGS84 / UTM zone 29 N reference system using the MODIS Reprojection Tool (MRT) version 4.1 (MRT, 2011). These composites were used to analyse ecosystem resilience after fire (Figure 2.22), as described further ahead (see 2.3.2).

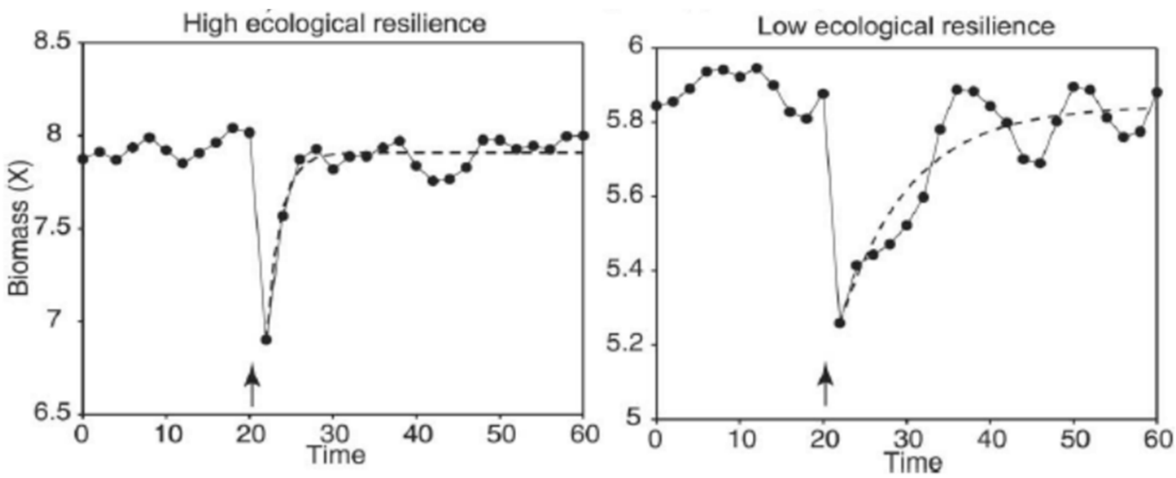


Figure 2.22 Contrasting responses of ecosystems after disturbance, in simulated pulse perturbation experiments. Sources: Nes and Scheffer (2007).

2.2.3.2. Pre-processing of the MODIS NDVI time series

Since remotely sensed, per-pixel time series of the Normalized Difference Vegetation Index (NDVI) can be hindered by noise from different sources (e.g. presence of clouds, varying sun-sensor-viewing geometries; Bradley *et al.*, 2007), we used a two-step blind rejection approach (i.e. without prior knowledge of the quality of the data) for data cleaning and smoothing, following Marcos *et al.* (2012), in order to remove spurious values: (i) firstly, we employed a filter based on the Hampel identifier (Hampel, 1974), considered rather effective (Pearson, 2002), which uses the concept of breakdown points based on local estimations of the median absolute deviation (MAD) and replaces the identified outliers with a local median; and (ii) secondly, we used a Savitzky-Golay filter (Savitzky & Golay, 1964), a type of filter that has been increasingly applied for cleaning, smoothing, and reconstruction of NDVI time series (Chen *et al.*, 2004; Heumman *et al.*, 2007), in order to further remove and replace spurious values. All computations for these cleaning and smoothing procedures were performed using the R programming environment, version 2.14.2 (R Development Core Team, 2012).

2.2.3.3. Calculation of burnt area statistics

In order to harmonize the spatial attributes of burnt areas (National Burnt Areas Database: 1990–2011; vector format) and of MODIS derived Ecosystem Functional Attributes (EFA; in raster format), a vector grid with 250 x 250m rectangular units (equal in pixel size and spatial extent to EFA data) was used to calculate the percentage of burnt area per year (between 2001 and 2011) within each unit. These calculations were performed using the PostgreSQL/PostGIS spatial database system (PostGIS, 2008). Burnt percentage data were later converted to raster format (for each year, considering a pixel size and a spatial extent equal to EFA data) to enable logic and algebraic operations.

2.2.3.4. Predictive variables

In total, 221 predictive variables were considered in the initial dataset and organized into several thematic blocks further detailed in the text below.

Fire traits – These are predictive variables detailing the magnitude and spatial characteristics of the previously selected burnt areas of year 2005 (Table 2.5). Analyses of spatial configuration and distribution of fire events were performed using ArcGIS (fstats_brn05_sum and dist_edge_m), and Fragstats (McGarigal *et al.* 2002) was used to compute spatial attributes of burnt patches.

Table 2.5 List of predictive variables related to traits of fire events / burnt areas.

Variable name/ acronym	Description	Type
breakMagnitudeIndex	NDVI post-fire break magnitude index	Fire magnitude/ intensity
fstats_brn05_sum_750m	Number of burnt pixels in a 750m buffer area	Fire spatial configuration
fstats_brn05_sum_1500m	Number of burnt pixels in a 1500m buffer area	Fire spatial configuration
fstats_brn05_sum_5000m	Number of burnt pixels in a 5000m buffer area	Fire spatial configuration
dist_edge_m	Distance to burnt patch edge (meters)	Fire spatial configuration
AREA_brt05	Burnt patch area (square-meters)	Fire spatial configuration
PERIM_brt05	Burnt patch perimeter (meters)	Fire spatial configuration
GYRATE_brt05	Burnt patch gyration index	Fire spatial configuration
PARA_brt05	Burnt patch perimeter-area ratio	Fire spatial configuration
SHAPE_brt05	Burnt patch shape index	Fire spatial configuration
FRAC_brt05	Burnt patch fractal dimension index	Fire spatial configuration
CIRCLE_brt05	Burnt patch circle index	Fire spatial configuration
CONTIG_brt05	Burnt patch contiguity index	Fire spatial configuration
CORE_brt05	Burnt patch core area (square-meters)	Fire spatial configuration
NCORE_brt05	Burnt patch number of disjunt core areas	Fire spatial configuration

CAI_brt05	Burnt patch core area index	Fire spatial configuration
PROX_brt05	Burnt patch proximity index	Fire spatial configuration
ENN_brt05	Burnt patch Euclidean nearest neighbor (meters)	Fire spatial configuration

Table 2.5 (cont.)

Fire history and trends – These are predictive variables related to historical fire recurrence, area and recent trends in burnt area, prior to year 2005 (Table 2.6). In order to analyze temporal proximity of fire activity in vegetation recovery processes, fire history variables were calculated considering three nested periods (1990-2004, 1995-2004 and 2000-2004), using the Portuguese National Cartographic Map of Burnt Areas (ICNF, 2012).

Table 2.6 List of variables related to fire history and trends prior to year 2005.

Variable name/ acronym	Description	Type
burnt_times_90_04	Number of fire events 1990-2004	Fire recurrence
burnt_times_95_04	Number of fire events 1995-2004	Fire recurrence
burnt_times_00_04	Number of fire events 2000-2004	Fire recurrence
mn_burnt_area_90_04	Mean burnt area 1990-2004	Total fire area
mn_burnt_area_95_04	Mean burnt area 1995-2004	Total fire area
mn_burnt_area_00_04	Mean burnt area 2000-2004	Total fire area
slope_lm_90_04	Burnt area trend 1990-2004	Fire area trend
slope_lm_95_04	Burnt area trend 1995-2004	Fire area trend
slope_lm_00_04	Burnt area trend 2000-2004	Fire area trend

Physical attributes – This set of variables contained information about the main environmental and physical attributes of the study area, such as geology/lithology, soil type, topography, hydrography, and climate (Table 2.7). Bioclimatic variables were calculated using the Digital Climatic Atlas of the Iberian Peninsula (Ninyerola *et al.*, 2005). Geological and soil variables were based on the Portuguese Environmental Atlas (APA, 2013), and topographic features were calculated from the ASTER GDEM version 2 elevation dataset (Tachikawa *et al.*, 2011).

Table 2.7 List of predictive variables related to physical attributes of the study area.

Variable name/ acronym	Description	Theme
bio_01	Annual Mean Temperature	Climate
bio_02	Mean Diurnal Range (Mean of monthly (max temp - min temp))	Climate
bio_03	Isothermality (BIO2/BIO7) (* 100)	Climate
bio_04	Temperature Seasonality (standard deviation *100)	Climate
bio_05	Max Temperature of Warmest Month	Climate
bio_06	Min Temperature of Coldest Month	Climate

bio_07	Temperature Annual Range (BIO5-BIO6)	Climate
bio_08	Mean Temperature of Wettest Quarter	Climate
bio_09	Mean Temperature of Driest Quarter	Climate
bio_10	Mean Temperature of Warmest Quarter	Climate
bio_11	Mean Temperature of Coldest Quarter	Climate
bio_12	Annual Precipitation	Climate
bio_13	Precipitation of Wettest Month	Climate
bio_14	Precipitation of Driest Month	Climate
bio_15	Precipitation Seasonality (Coefficient of Variation)	Climate
bio_16	Precipitation of Wettest Quarter	Climate
bio_17	Precipitation of Driest Quarter	Climate
bio_18	Precipitation of Warmest Quarter	Climate
bio_19	Precipitation of Coldest Quarter	Climate
rock_type	Main/dominant rock type	Geology/Lithology
soil_name	Dominant soil type/class	Soils
soil_subname	Sub-dominant soil type/class	Soils
elev_m	Mean Elevation (meters)	Topography
slope_perc	Slope (percentage)	Topography
curv	Surface curvature	Topography
aspect_ang	Aspect (angle)	Topography
asp_class	Main aspect class (north, east, south, west and flat)	Topography
asp_north	Northness (cosine transformation)	Topography
asp_east	Eastness (sine transformation)	Topography
twi	Topographic Wetness Index	Topography

Table 2.7 (cont.)

Landscape composition – This set of predictors details aspects related to the composition of landscape mosaics for each 250x250m grid cell as well as its surrounding area. We used a reclassified version of the Corine Land Cover 2000 database (revised version) for mainland Portugal (Caetano *et al.*, 2009a,b) to calculate the percentage cover of eight broad land cover/use classes (Table 2.8). The CLC reclassification matrix is available in Appendix 1. Additionally, in order to study neighborhood effects on vegetation recovery processes, we calculated the percentage cover of the eight classes using three different buffer distances (750m, 1500m and 5000m) around each grid square. These calculations were implemented in PostgreSQL/PostGIS spatial database system (PostGIS, 2008).

Table 2.8 List of predictive variables related to landscape composition. Each of these eight variables was computed for three buffer distances around each grid cell.

Variable name/ acronym	Description	Type
CLC1	Percentage cover of Urban/Artificial areas	Landscape composition
CLC2	Percentage cover of Agricultural areas	Landscape composition
CLC3	Percentage cover of Broad-leaved forest	Landscape composition

CLC4	Percentage cover of Coniferous forest	Landscape composition
CLC5	Percentage cover of Mixed forest	Landscape composition
CLC6	Percentage cover of Scrub and/or herbaceous vegetation associations	Landscape composition
CLC7	Percentage cover of Open spaces with little or no vegetation	Landscape composition
CLC8	Percentage cover of Wetlands/water bodies	Landscape composition

Table 2.8 (cont.)

Using this dataset we performed a characterization of the total study area as well as of burnt areas in terms of land cover (LC), by calculating cover percentages of all LC categories (see Appendix 1). To assess whether land cover changes expressed in the CLC database would reflect those expected to originate from fire disturbance, alteration statistics for each broad CLC category were calculated between years 2000 and 2006 (Table 2.9). These statistics were computed for the whole study area as well as for areas burnt in the focal year (2005; Figure 2.23).

Table 2.9 Cross-tabulation of land cover (in %) between years 2000 (columns) and 2006 (rows), based on aggregated CLC data for the whole study area.

		Year 2006							
		Urban/ Artificial	Agricultural areas	Broad-leaved forest	Coniferous forest	Mixed forest	Scrub and/or herbaceous vegetation	Open spaces with little or no vegetation	Wetland s/water bodies
Year 2000	Urban/Artificial	99.3	0	0	0	0	0.7	0	0
	Agricultural areas	0.1	97.2	0	0	0	2.6	0.1	0
	Broad-leaved forest	0.1	0	11.7	0.1	0.3	86.1	1.7	0
	Coniferous forest	0.2	0	0	7	0.2	87.2	5.4	0
	Mixed forest	0.2	0	0.1	0.3	15.3	83	1.2	0
	Scrub and/or herbaceous vegetation	0.2	0	0.1	0.1	0	94.5	5.0	0
	Open spaces with little or no vegetation	0	0.1	0	0	0	9.8	90.1	0
	Wetlands/water bodies	0.0	0.0	0.0	0.0	0.0	0.0	0.0	100.0

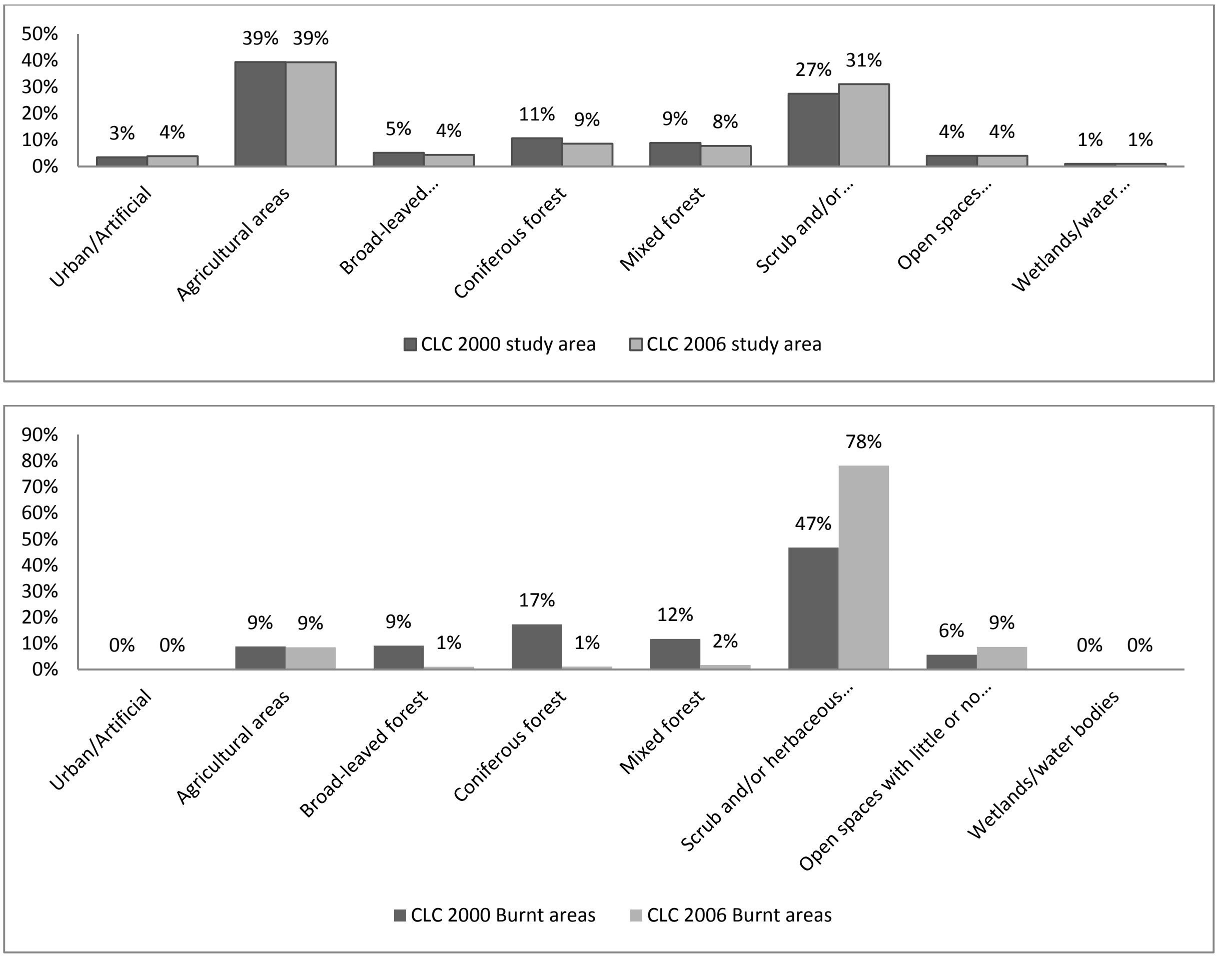


Figure 2.23 Relative (%) land cover (CLC) in years 2000 and 2006, for the total study area (top) and for areas burnt in year 2005 (bottom).

For the entire study region, there were strong declines in forested areas (-19.1% in coniferous forests, -14.8% in broad-leaved forests, and -12,5% in mixed forest areas). This was accompanied by an increase of 13.0% in the area of scrub/heathlands. Urban/artificial areas also recorded an increase in this time interval close to 11.2% (Figure 7, top). In the case of 2005 burnt areas (Figure 7, bottom), similar land cover transitions have occurred with very strong losses recorded for forest areas (all types). In these areas (totaling a surface of 1622 km^2), coniferous, mixed and broad-leaved forest areas have decreased by 263 km^2 (-93.2%), 163 km^2 (-85.2%) and 131 km^2 (-88.0%), respectively. Conversely, an increase was observed for scrub/heathlands (67.1%) and open spaces with little or no vegetation (54.2%). Although forest areas were severely affected by fires in year 2005, a large proportion of burnt area, roughly 46.8%, occurred on scrub or heathlands areas.

Overall, these structural (land cover) changes suggest that CLC data are suitable to analyze the effects of wildfires on land cover composition patterns at the regional scale, and so the predicting variables derived from this dataset were included in the modeling routines (see below).

Pre-fire conditions and attributes of ecosystem functioning – This group includes those variables describing pre-fire ecosystem attributes such as those related to productivity, seasonality, phenology and greenness trends. All of these variables were calculated from annual NDVI time-series from the available pre-fire interval (2001-2004). The extraction of ecosystem functional attributes from temporal profiles of remote sensing-derived variables (e.g. vegetation indices like NDVI) has gained considerable attention in recent years (e.g. Alcaraz-Segura *et al.*, 2006; Leeuwen *et al.*, 2010; Bastos *et al.*, 2011). To describe functional aspects of the flux of energy in ecosystems, and the patterns of the interception of radiation by vegetation, three attributes were extracted from the seasonal NDVI curve of each year: productivity, seasonality and phenology (Alcaraz-Segura *et al.*, 2006). These three attributes describe in an adequate way the height and shape of the annual NDVI curve and they have been shown to have biological significance (Pettorelli *et al.*, 2005).

Table 2.10 lists the variables used to describe those three attributes. As indicators of productivity, the mean and median values, as well as the maximum and minimum values for each year, were computed. For seasonality, we calculated the range (i.e. the difference between the maximum and minimum values), the standard deviation, the median absolute deviation, the coefficient of variation (i.e. the standard deviation divided by the mean), a non-parametric coefficient of variation (i.e. the median absolute deviation divided by the median), the relative range (i.e. the difference between the maximum and minimum values, divided by the mean), and the non-parametric relative range (i.e. the difference between the maximum and minimum values, divided by the median). Finally, as indicators of phenology, we calculated the time (i.e. the 16-day maximum value composite) in which the maximum and the minimum values of each year occurred, as well as the difference between those two values, as an indicator of the length of the growing season.

Furthermore, we applied transformations to the original variables, such as the base 10 logarithm and the negative base 10 logarithm to some of the seasonality-related variables. We also computed the "springness" and "winterness" of the phenological variables, by transforming the original variables into polar coordinates and characterizing them by their sine and cosine values, respectively, in order to keep the continuous nature of the annual period and the relative distance between the times of the year (i.e. December is as close to January as July is to June) (Alcaraz-Segura *et al.*, 2006).

From the variables present in Table 2.10, the mean and median were calculated when possible, as an example from the Minimum variable the mean minimum productivity was calculated and the suffix MN was added (min_MN), when we calculated the median minimum productivity we added the suffix MD (min_MD).

Preliminary tests confirmed that these variables are sensitive to the changes caused by wildfire. As an example, Figure 2.24 illustrates that the NDVI coefficient of variation and the NDVI median suffered changes in the focal year (2005) in burnt pixels, compared with neighboring non-burnt (control) areas.

Table 2.10 List of predicting variables used to describe pre-fire ecosystem functional attributes in this study.

Name/acronym	Description	Attribute
mean	Mean (i.e. average)	Productivity
median	Median	Productivity
min	Minimum	Productivity
max	Maximum	Productivity
range	Range (max - min)	Seasonality
sdev	Standard deviation	Seasonality
mad	Median absolute deviation	Seasonality
cov	Coefficient of variation	Seasonality
lcov	Base-10 logarithm of the coefficient of variation (log10(cov))	Seasonality
pcov	Negative base-10 logarithm of the coefficient of variation (-log10(cov))	Seasonality
npcov	Non-parametric coefficient of variation (median / mad)	Seasonality
rrel	Relative range ((max - min) / mean)	Seasonality
nprrel	Non-parametric relative range ((max - min) / median)	Seasonality
dmax	Time (i.e. 16-day composite) of maximum	Phenology
dmax_winterness	“Winterness” ((cos(dmax – 36) / 23) * (2 * pi) * (360 / 365)) of the time of maximum	Phenology
dmax_springness	“Springness” ((sin(dmax – 36) / 23) * (2 * pi) * (360 / 365)) of the time of maximum	Phenology
dmin	Time (i.e. 16-day composite) of minimum	Phenology
dmin_winterness	“Winterness” ((cos(dmax – 36) / 23) * (2 * pi) * (360 / 365)) of the time of minimum	Phenology
dmin_springness	“Springness” ((sin(dmax – 36) / 23) * (2 * pi) * (360 / 365)) of the time of mminimum	Phenology
length	Proxy of length of the growing season (abs(dmax - dmin))	Phenology
percentIncrease2004	NDVI percent increase in pre-fire year 2004	Pre-fire trend
ndviTrends20012004slope	NDVI 2001-2004 trend slope (Theil-Sen estimator)	Pre-fire trend

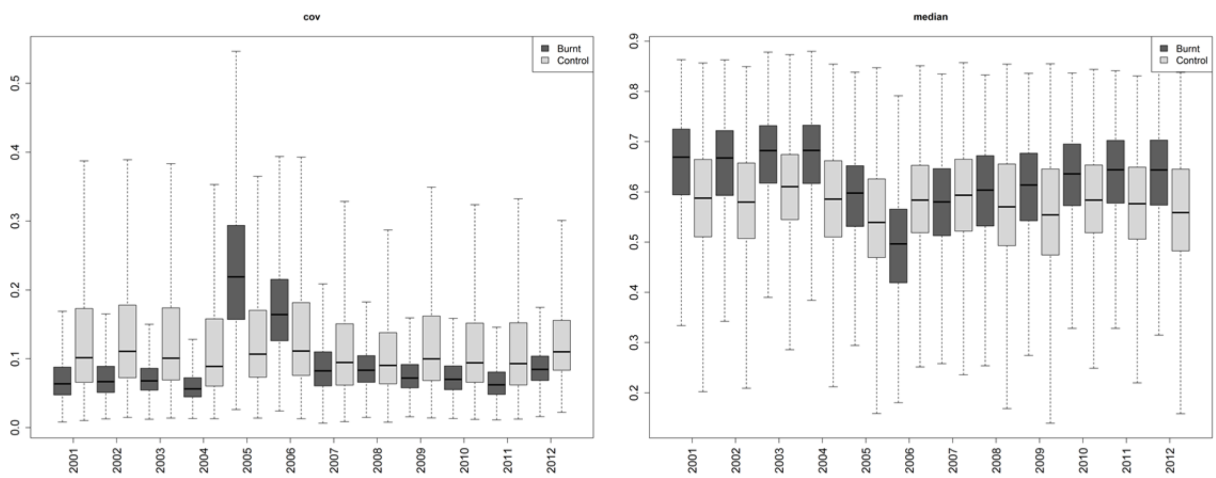


Figure 2.24 Inter-annual changes in the functional attributes of burnt and control areas, between years 2001 and 2010: (left) NDVI coefficient of variation (cov); (right) NDVI median.

2.2.4. Sub-regional level: Alto Minho

In the study of wildfire patterns in the Alto Minho region, in addition to the national fire database (see 2.2.1) and other national databases on environmental, landscape, socioeconomic and topographic factors (see 2.2.2), the most important database was a regional land cover map produced for year 2000 (1:25 000), through GIS interpretation of ortho-photomaps, by the Instituto Politécnico de Viana do Castelo (used here by courtesy of Joaquim Alonso, IPVC), following the methodology and land cover classification used by the Portuguese Geographic Institute in the COS´90 national coverage (IGEO).

For each of the 13 960 land cover patches in the study area, two types of information were computed: values for several variables known to affect wildfire patterns (as described in previous sections; Table 2.11; Figure 2.25), and a burnt percentage per year (Table 2.12).

Table 2.11 Set of explanatory variables used to characterize every land cover patch in the study area (name, description, group and source).

variable name	description	variable group	source
land cover	land cover class of the patch	Land cover	IPVC (2007)
area_p_m2	patch area	Area	IPVC (2010)
distroad	distance to roads	Distance	Instituto das Estradas de Portugal
driver	distance to river		Agência Portuguesa do Ambiente (2010)
mslope	mean slope	Topography	USGS (2006)
aspect	aspect (North, South, East, West)		
malt	mean altitude		
bio1	Annual Mean Temperature	Climate	WORLDCLIM Hijmans et al, 2005, 2005
bio2	Mean Diurnal Range (Mean of monthly (max temp - min temp))		
bio3	Isothermality (BIO2/BIO7) (* 100)		
bio4	Temperature Seasonality (standard deviation *100)		
bio5	Max Temperature of Warmest Month		
bio6	Min Temperature of Coldest Month		
bio7	Temperature Annual Range (BIO5-BIO6)		
bio8	Mean Temperature of Wettest Quarter		
bio9	Mean Temperature of Driest Quarter		
bio10	Mean Temperature of Warmest Quarter		
bio11	Mean Temperature of Coldest Quarter		
bio12	Annual Precipitation		
bio13	Precipitation of Wettest Month		

bio14	Precipitation of Driest Month		
bio15	Precipitation Seasonality (Coefficient of Variation)		
bio16	Precipitation of Wettest Quarter		
bio17	Precipitation of Driest Quarter		
bio18	Precipitation of Warmest Quarter		
bio19	Precipitation of Coldest Quarter		

Table 2.11 (cont.)

Table 2.12 Burnt percentage in each land cover patch for the analyzed time frame (2000-2010) (only an illustrative set of patches is shown from the 13960 total set of patches).

Year/ Patch Id	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Total
10294	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	82.7	0.0	82.7
9308	0.0	0.0	0.0	0.0	82.8	0.0	0.0	0.0	0.0	0.0	82.8
1815	0.0	0.0	0.0	0.0	0.0	0.0	0.0	42.5	40.3	0.0	82.8
9298	0.0	82.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	82.8
8090	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	82.9	82.9
9309	0.0	0.0	0.0	0.0	0.0	82.9	0.0	0.0	0.0	0.0	82.9
10919	0.0	0.0	0.0	0.0	0.0	83.0	0.0	0.0	0.0	0.0	83.0
941	9.9	0.0	1.1	0.0	72.0	0.0	0.0	0.0	0.0	0.1	83.1
1348	83.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.1

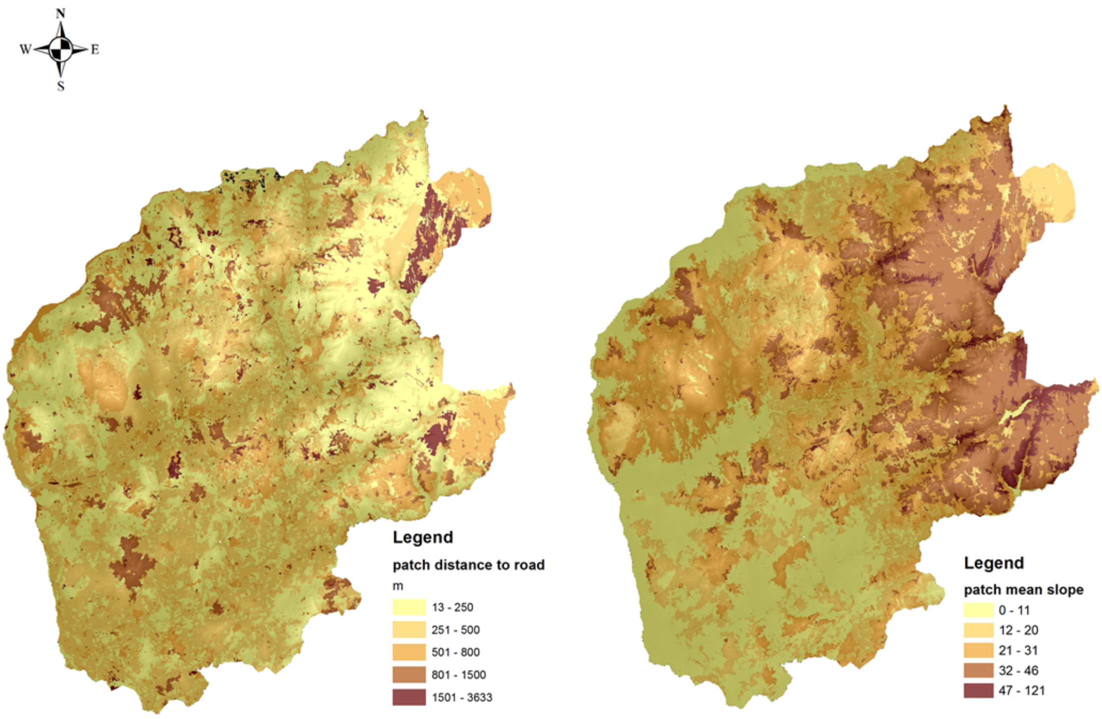


Figure 2.25 Two examples of the predictive variables computed for each land cover patch: (left) Patch distance to roads; (right) Patch mean slope. Source: derived from COS'90 (IGEO).

2.2.5. Municipality level: Baixo Tâmega

New data on vegetation and plant community structure was collected in the Baixo Tâmega municipalities during Spring 2008 to assess the local drivers of post-fire resilience. Since the emphasis was on assessing the relative importance of fire history and geological factors as drivers of vegetation recovery, the sampling was stratified according to three binary variables: (1) fire frequency (a single fire vs. two or more fires since 1990), (2) time since last fire (10 or fewer years vs. more than 10 years), and (3) Lithology (granite vs. schist). Five sites corresponding to scrubland areas, according to a land cover map of year 2000 (Honrado and Vieira, 2009) and visual inspection of aerial photographs, were then randomly selected inside each of the resulting eight strata. In order to control the effects of climate variations, only areas with elevation between 700m (corresponding to the lower elevation limit of mountainous areas in Portugal; Aguiar *et al.*, 2010) and 1000m were considered. These corresponded to a total of 811 land cover patches, from which the 40 surveyed sites were selected under a stratified random sampling strategy (Figure 2.26).

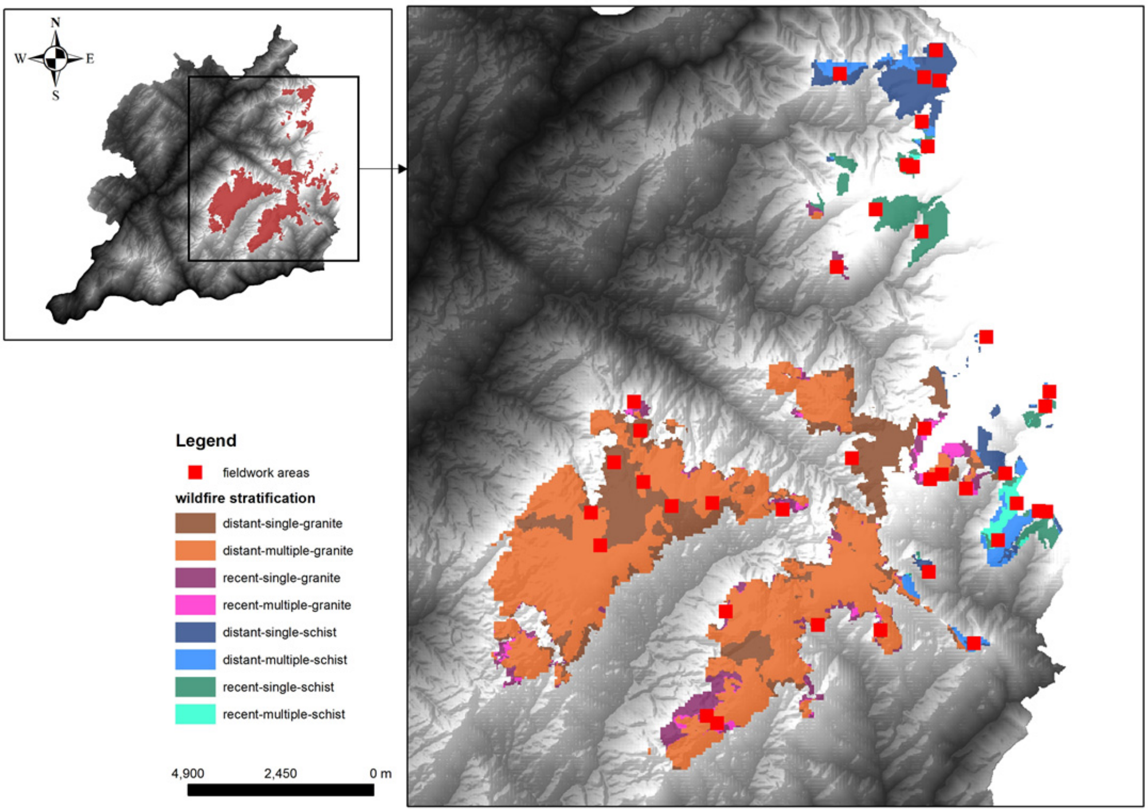


Figure 2.26 Stratified random sampling of 40 sites from which new vegetation and plant community data were collected in the Baixo Tâmega municipalities.

In-field campaigns consisted of collecting vegetation and plant community data from a 25m^2 plot at each of the 40 locations. An area with homogeneous vegetation cover was selected at, or close to, each geographic point. A standardized field protocol and recording form (see Appendix 2) was followed to collect harmonized information on vegetation structure and on plant community structure.

Vegetation structure was recorded based on the height and percentage cover of three vertical strata: tall shrubs (i.e. woody plants >2m tall; E1), low shrubs (i.e. woody plants <2m and >0.6m tall; E2), and herbs (i.e. herbaceous plants; E3). From the data on vegetation structure, the following six response variables were later computed for each plot: height of stratum E1, height of stratum E2, height of stratum E3, cover of stratum E1, cover of stratum E2, and cover of stratum E3.

Data on plant community structure allowed the calculation of an additional set of response variables related to: (1) total species richness per plot, and (2) species richness per plot for each functional group (woody species only). For the later, plant species were grouped according to the five classifications described in Table 2.13. Also, species composition data were used to assess community assembly and its underlying gradients through multivariate statistics (see section 2.3.4).

Table 2.13 The five classifications used to group woody plant species and compute species richness per functional group.

Classification	Group label	Group name	Group description	References
Leaf strategy	DEC	Deciduous	Species with deciduous leaves	Bunce et al, 2008
	EVR	Evergreen	Species with evergreen leaves	
	NLE	Non-leafy	Species with no or ephemeral leaves	
Life forms	FOR	Trees	Species with height usually above 2m	Bunce *et al.* (2008)
	TAL	Tall shrubs	Species with height usually between 0.6 and 2m	
	LOW	Low shrubs	Species with height usually below 0.6m	
Response to disturbance	s	Seeders	Species recovering from disturbances through seed germination	Gill (1981)
	r	Resprouters	Species recovering from disturbances through resprouting from basal organs	
Seed dispersal	ANE	Anemochoric	Species dispersing seed passively by wind	Pijl (1972)

	BAR	Barochoric	Species dispersing seed passively by gravity alone	
	ZOO	Zoochoric	Species dispersing seed actively by animals	
Synecology	fed	Forests and edges	Species with forests or edges as their primary habitats	Honrado (2003)
	tsc	Tall scrub	Species with tall scrub as their primary habitat	
	lsc	Low scrub	Species having low scrub as their primary habitat	

Table 2.13 (cont.)

2.3. Statistical analyses, modelling, and workflows

2.3.1. National patterns and drivers of wildfire occurrence

2.3.1.1. General approach and workflow

The assessment of the spatiotemporal patterns of wildfire occurrence in mainland Portugal was done through the application of several modelling techniques to a national comprehensive database. The workflow included the following sequential steps:

(1) Construction of the national database, with calculation, for each civil parish, of values for the response variable (burnt proportion) and for 80 predictor variables potentially valuable to explain the detected patterns;
(2) Extensive model calibration with use of five different algorithms, each one with several different settings in order the find the model with the best performance; and
(3) Analysis of model results with evaluation statistics, and interpretation of the results.

Due to the lack of land cover data, some civil parishes were excluded from the analysis (Figure 2.25, right).

With the intention of testing whether the country had a common national level set of drivers of fire history, or then regionally stratified sets of drivers, we subdivided the dataset using the seven Portuguese statistical agrarian regions: [EDM] Entre Douro e Minho, [TM] Trás-os-Montes, [BL] Beira Litoral, [BI] Beira Interior, [RO] Ribatejo e Oeste, [ALT] Alentejo, and [ALG] Algarve (Figure 2.27, left).

These statistical regions were used because they provide a simple and parsimonious division of the Portuguese territory (considering its climatic, socioeconomic, and land use and landscape variations) and also because they are used as statistical units by the institutes of the administration that collected part of the data used in the analyses (INE, 2010). When using these statistical regions, the purpose was to generate subsets of data in order to evaluate a possible "regionalization" of fire history, and so all the different subsets and all the analyses were developed at the best common spatial grain available (i.e. the civil parish).

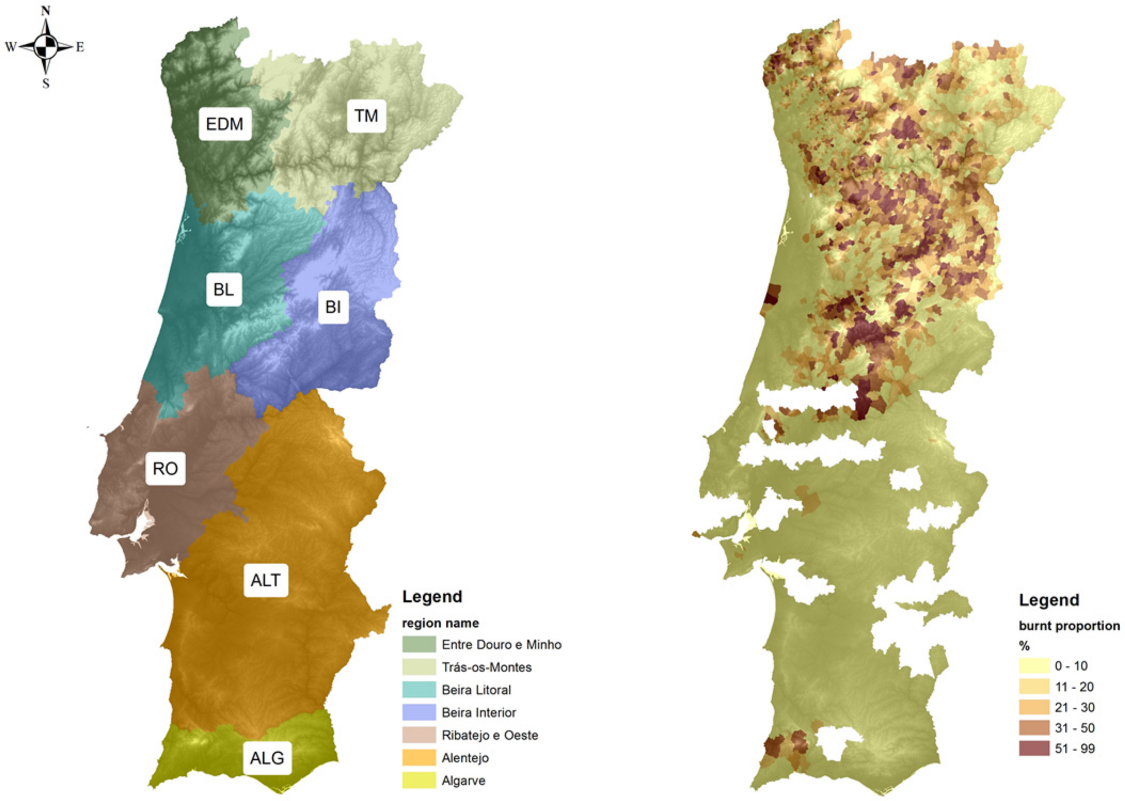


Figure 2.27 (left) Cartographic representation of the seven Portuguese statistical agrarian regions; (right) Map of the civil parish burnt proportion (the response variable in modelling routines) in those parishes for which a complete dataset was available. Sources: (left) …, (right) …

2.3.1.2. Response variables

In this study of wildfire patterns and drivers, response variables were related to fire history and were derived from the national wildfire database (see section 2.2.1). Specifically, the response variable used in this study was the burnt proportion per civil parish, computed as the cumulative area burnt in the focal period divided by the total area of the civil parish (see Figure 2.27, right).

2.3.1.3. Computation of datasets

In total, 40 datasets were generated, corresponding to the predictive tasks described further below. These datasets shared two common problems:

- Some cases (i.e. civil parishes) had variables for which the values are not known (e.g. the land cover information);

- Some of the agrarian statistical regions had too few samples (i.e. civil parishes with adequate available data), leading to some situations where the number of predicting variables was higher than the number of cases, which is known to cause problems when using most modeling techniques.

To try to overcome these problems, we used the following three-step heuristic method:

1. We removed from the dataset any variable with more than 100 unknown values;
2. For the remaining variables, we used random forests (see Breiman (2001) for a full description, namely of the use of random forests for estimating variable importance) for calculating each variable's capability of explaining the patterns of the response variable, obtaining a score for each variable; based on this score we selected the 50% of variables with the highest overall importance;
3. In this final set of independent variables to use in each predictive task, we removed any case (i.e. civil parish) that had unknown values for any of these variables.

This heuristic process has yielded 40 datasets with only a sub-set of the original independent variables and civil parishes, but with no unknown variable values.

2.3.1.4. The prediction tasks

These several datasets were derived using the available data with the ultimate goal of explaining and predicting the percentage of burnt area per civil parish in continental Portugal and in its seven statistical agrarian regions. These datasets supported different prediction tasks that had in common the response variable, though they varied in terms of both the explanatory variables that were used and the cases (i.e. civil parishes) that were included in the datasets.

Two types of analyses were performed, either using all available data (from all regions of the country together), or then using only the data for each one of the seven agrarian regions. Summarizing, we have considered in our analysis 40 different prediction tasks: 8 different sets of data/observations (whole country plus each of the seven regions), multiplied by 5 different sets of explanatory variables (i.e. climatic, demographic, landscape, topographic, or all variables together; see section 2.2.2).

For each of these prediction problems we considered the use of different modelling techniques with the goal of estimating the predictive performance to explain the observed patterns of the response variable. From a modelling perspective, the assumption here was that by observing the behaviour of this predictive performance we would be able to answer the research questions underlying this study based on the most robust combination of data and modelling technique.

2.3.1.5. Modelling techniques

With the goal of removing any possible bias from our conclusions concerning the choice of the modelling techniques, we have tried to select and apply a diverse set of approaches. Namely, in each of the 40 prediction tasks we tested the use of:

- Multiple linear regression models (Draper and Smith, 1998),
- Generalized linear models (McCullagh and Nelder, 1989),
- Regression trees (Breiman *et al.*, 1984),
- Support vector machines (Shawe-Taylor and Cristianini, 2000), and
- Random forests (Breiman, 2001).

Moreover, for most of these techniques several parameter variants were used in the experiments.

Overall, the modeling technique with the best results in the performed tests was Support Vector Regression (SVR), which was therefore used in all further analyses to disentangle the factors behind fire history in Portugal and in the several statistical regions. A brief description of this technique is therefore provided in the next paragraphs, and in the following sections we will only describe the procedures involved in SVR.

Smola and Scholkopf (1998) published a fundamental tutorial giving an overview of the basic ideas underlying SVM for function estimation. Vapnik (1998), and Shaw-Taylor and Cristianini (2000) are two essential references for SVM. These are complemented with the work of Karatzouglou (2006) for implementing an SVM and kernel method environment in R Language.

In Support Vector Regression (SVR) the basic idea is to map the data x into a high dimensional feature space F via a nonlinear mapping Φ and obtain a linear regression model in this new space:

$$\boldsymbol{f}(x) = (\omega \cdot \Phi(x)) + b$$

with $\Phi : R^n \rightarrow F$, $\omega \in F$, where b is a threshold.

Thus, linear regression in a high dimensional (feature) space corresponds to non–linear regression in the low dimensional input space Rn. Since Φ is fixed, ω is determined from the data by minimizing the sum of empirical risk Remp [f] and a complexity term ||ω||2, which enforces flatness in the feature space:

$$R_{reg}[f] = R_{emp}[f] + \lambda\|\omega\|^2 = \sum_{i=1}^{l} C\,(f(x_i) - y_i + \lambda\|\omega\|^2$$

where l denotes the sample size, C (.) is a cost function (e.g. Vapnik's (1998) insensitive loss function), and λ is a regularization constant.

For a large set of cost functions, the previous equation can be minimized by solving a quadratic programming problem, which is uniquely solvable. It is possible to write the vector ω in terms of the data points:

$$f(x) = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*)(\phi(x_i))$$

with αi ,α∗ being the solution of the afore–mentioned quadratic programming problem.

The problem may be rewritten as products in the low dimensional space:

$$\omega = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*)(\phi(x_i).\phi(x)) + b = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*)K(x_i, x) + b$$

In the above equation the kernel function is introduced: K (xi, xj) = (Φ(xi)• Φ(xj)).

It can be shown that any asymmetric kernel function, K, satisfying Mercer's condition, corresponds to a dot product in some feature space. A common kernel is a Radial Basis Function (RBF) kernel:

$$K(x_i, x_j) = exp\,(-\gamma.\|x_i - x_j\|^2)$$

being *γ* the width of Vapnik's (1998) insensitive loss function.

2.3.1.6. Tuning SVR

The R software package contains the *ksvm* function that is mostly programmed in R but uses the optimizers found in *bsvm* and *libsvm*, which provide a very efficient C++ version of the sequential minimization optimization (SMO).

In our comparative study, we have focused on variants of the epsilon insensitive loss function (gamma argument). By default, this value is 0.1, but in our trials we have used the values 0.01, 0.001 and 0.0005. Different values of parameter cost were also used in our experiments: 100, 200 and 500. In summary, we have considered 9 variants of SVR models.

2.3.1.7. Evaluation statistics

The models obtained by these different techniques were evaluated in terms of their predictive accuracy using the Normalized Mean Absolute Deviation (NMAD), which is given by:

$$nmad = \frac{\sum_i^n = 1|\hat{y_i} - y_i|}{\sum_i^n = 1\,|\bar{y} - y_i|}$$

where n is the number of test cases, $\bar{y}$ is the response value of case i, $\hat{y_i}$ is the prediction of the model for the case i, and y is the average response value estimated with the given dataset (Hoaglin *et al.*, 1983).

With the aim of providing unbiased estimates of the predictive performance of the different models across the 40 prediction tasks, a Cross Validation (CV) estimation process was followed. Namely, 3 repetitions of a 10-fold CV experiment were carried out with all modelling techniques on the 40 tasks. This experimental process was used to estimate the average NMAD of each technique for each problem. Moreover, paired Wilcoxon signed rank tests were used to assert the statistical significance of the observed differences.

2.3.2. Regional patterns of post-fire resilience in northern Portugal

2.3.2.1. General approach and workflow

The assessment of the spatiotemporal patterns of post-fire ecosystem resilience in northern Portugal was performed through the analysis of post-fire ecosystem functional attributes against several groups of potentially predictive variables. The spatial setting for this analysis was established based on the availability of remote sensing data as well as on a set of previous structural analyses of burnt areas in the focal period.

The general workflow included the following sequential steps:

(1) Selection of burnt areas;

(2) Computation of response variables (post-fire attributes of ecosystem functioning

as proxies of ecosystem resilience);
(3) Model calibration and evaluation;
(4) Assessment of importance of response variables; and finally
(5) Analysis of selected response curves.

2.3.2.2. Selection of burnt areas

Raster algebra was used to select burnt areas that were suitable for the objectives of this study. Consider B_i a raster dataset containing the percentage of burnt area for year i and S a Boolean raster dataset containing the selected areas (or test areas). Also consider $s_{m,n} \in \{0,1\}$ a pixel within this dataset with values in the Boolean range.

$$S = (B_{2005} \geq 75\%) \cap (B_{2001} < 25\% \cap B_{2002} < 25\% \cap B_{2003} < 25\% \cap B_{2004} < 25\% \cap B_{2006} < 25\% \cap B_{2007} < 25\% \cap B_{2008} < 25\% \cap B_{2009} < 25\% \cap B_{2010} < 25\% \cap B_{2011} < 25\%)$$

This operation allowed selecting grid cells that burned 75% or more of their surface area in year 2005 (i.e. cells that were heavily affected by wildfires in this year) and that remained unburned or only mildly affected by fire (up to a threshold of 25% of the pixel area) in the remaining years within the 2001-2011 time span of the study (excluding 2005). Grid cells selected by these conditions were the ones used in this study of post-fire regeneration.

2.3.2.3. Computation of response variables

In order to assess post-fire vegetation recovery in the study area, we used the NDVI values between 2006 and 2010, for each pixel in which there was a fire in year 2005 (and in which, according to the fire database, no other relevant fires occurred in any other year between 2001 and 2010; see section 2.2.3), to compute the following two indices of relative vegetation recovery:

(i) the Recovery Trend Index (RTI) was computed as the slope of the trend in the NDVI data for the 2006-2010 period, by using the Theil-Sen's estimator, which is a rank-based test that is robust against non-normality of the distribution and missing values (Theil, 1950); unlike the Mann–Kendall test, this estimator not only detects if a trend exists, but also provides the amplitude of that trend (Sen, 1968); we used the R package zyp (Bronaugh and Werner, 2009), which accounts for inter-annual autocorrelation present in the data;

(ii) the Cumulative Relative Recovery Index (CRRI) was calculated as the sum of the relative recovery values in the 2006-2010 period (obtained by dividing each NDVI value in that period by the difference between the 2001-2004 inter-annual median value and the minimum NDVI value in 2005), standardized by the number of values, in order to get a gradient from 0% (i.e. no recovery) to 100% (i.e. total recovery).

Estimates of the rate of recovery of the vegetation were also computed by fitting non-linear models based on the methodology described in Bastos *et al.* (2011), which consists in defining a “Gorgeous Year” against which the anomalies in the fire and post-fire years are calculated (in this case, the median values for 2001-2004 were used), with the objective of reducing inter-annual phenological variability, thereby allowing estimating the recovery rate by means of regression analysis. Using this methodology, we estimated recovery times (in days) for 50%, 75% and 95% of the pre-fire median levels (RT50, RT75 and RT95, respectively), which can be viewed as the time when the modelled curve of vegetation recovery crosses the threshold defined as either 50%, 75% or 95% of the median value over the pre-fire period (i.e. 2001-2004; see Bastos *et al.*, 2011). Since the performance of the models fitted for the 75% and 95% recovery time where very low, hereafter we will only refer to the 50% recovery time model.

Finally, three response variables were selected for further analyses (Figure 2.28): the Recovery Trend Index (RTI), the Cumulative Relative Recovery Index (CRRI), and the 50% Recovery Index (RT50). The R package nls2 (Grothendieck, 2013) was used to fit non-linear models for the computation of these three response variables.

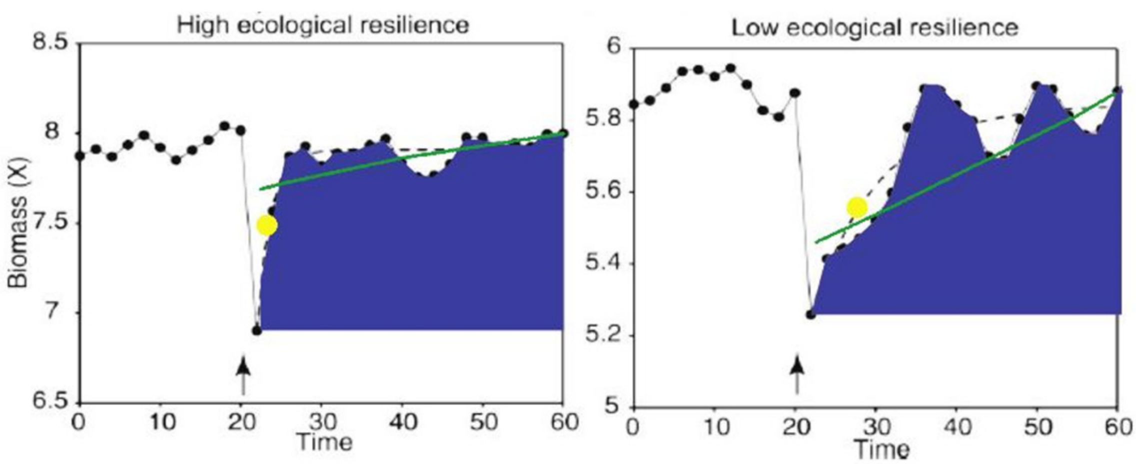


Figure 2.28 Representations of the three response variables for two contrasting resilience levels (see also Figure 2.22): the Cumulative Relative Recovery Index (CRRI; blue area), the Recovery Trend Index (RTI; green line) and the 50% Recovery Index (RT50; yellow dot).

The statistical correlations among these three indicators of ecosystem resilience are described in Table 2.14.

Table 2.14 Spearman's correlation scores between pairs of response variables.

	Recovery Trend index	Cumulative Relative Recovery Index	50% Recovery Time
Recovery Trend index	-	0.349	0.599
Cumulative Relative Recovery Index	0.349	-	-0.100
50% Recovery Time	0.599	-0.100	-

It must be stressed that this definition of vegetation recovery based on ecosystem functional attributes only refers to the re-establishment of pre-fire chlorophyll levels, or vegetation density (vegetation greenness), and therefore it does not account for either the recovery of the ecosystem's structure or diversity, as it does not for individual tree or species development.

2.3.2.4. Model calibration and evaluation

In order to relate post-fire recovery response variables and predicting variables, for the model fitting tasks we used the Random Forest (RF) algorithm (Breiman, 2001), implemented in R's *randomForest* package (Liaw and Wiener, 2002). The RF algorithm has shown excellent performance in high dimensionality situations, where sometimes the number of predicting variables is much higher than the number of observations, for their ability to handle with complex interaction structures as well as highly correlated variables, and it can provide measures of variable importance (Oppel *et al.*, 2009; Boulesteix *et al.*, 2012). In wildfire studies, the RF algorithm has been successfully applied, among other, in determining fire severity from satellite data (Holden *et al.*, 2009), modelling and mapping forest canopy fuels for fire behavior analysis (Pierce *et al.*, 2012), or modelling spatial patterns of fire occurrence in the Mediterranean area (Oliveira *et al.*, 2012). Random forest parameterization used a *mtry* value equal to 70, *ntree* equal to 100, and no replacement. Other parameters were set to default.

In order to assess model performance we used Monte Carlo cross-validation – MCCV (Qing-Song, 2004), by splitting our initial dataset (containing 20 650 observations and 221 predictors) into two separate datasets, i.e., a training set containing 30% of the observations (totaling 6195) and a test set with 70% (14 455). This cross-validation method and the relatively small number of training observations were defined in order to decrease RF computation time for each replicate. For each response variable, 100 RF models (i.e., replicates) were generated. All results, including model predictions, performance statistics and variable importance measures, were then averaged across replicates.

As performance measures between observed (y_i) and predicted values ($\hat{y_i}$) we used R^2, Root-mean-square Error (RMSE), the Normalized Root-mean-square Error (NRMSE), and the Pearson Correlation:

$R^2 = 1 - \frac{\sum_{i=1}^{n}(\hat{y_i}-y_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y_i})^2}$, where $\bar{y_i}$ equals the average of observed values

$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i-\hat{y_i})}{n}}$, with n equal to the number of test observations

$NRMSE\% = \left(\frac{RMSE}{y_{max}-y_{min}}\right) \times 100$, where $y_{max} - y_{min}$ is the range of observed values

2.3.2.5. Importance of predicting variables

To evaluate the importance of individual predictive variables, we used the function *importance*(), also implemented in the *randomForest* package, using parameter “type=2” which calculates importance as the total decrease in node impurities from splitting each variable, averaged over all trees. For regression, node impurity is measured by the residual sum of squares. We set the parameter “scale=FALSE” as suggested in Strobl and Zeileis (2008). Overall, the variable importance assessment focused on the relative ranking of variables instead of absolute contribution to prediction accuracy.

2.3.2.6. Response curves

Response curves (or evaluation strips), obtained using univariate models fitted for the best predictive variables for each response variable, were used to investigate the post-fire ecological response of burnt areas to variations in those predictors. The computation of these curves was based on Elith (2005) and they were calculated by fitting 100 univariate models, each one with 5% of the total number of observations in the dataset (to decrease computational time), and then by averaging prediction results.

2.3.3. Assessing wildfire patterns and drivers in the Alto Minho

2.3.3.1. General approach and workflow

The assessment of the spatiotemporal patterns and drivers of wildfire occurrence in the Alto Minho sub-region, northwest Portugal, was done through the application of machine learning algorithms, namely Inductive Logic Programming, at the burnt patch level, to a region with very high burnt areas and wildfire recurrence. The workflow included the following sequential steps:

(1) Construction of a patch level database with relevant variables for modelling fire history for the periods 1991-2000 and 2001-2010;
(2) Use of the database in an ILP context to construct a set of rules that try to explain the fire history in the training period (1991-2000); and
(3) Validation of the rule set with an independent test dataset, corresponding to fire history in the period 2001-2010.

2.3.3.2. Response variables

In this study of wildfire patterns and drivers, the response variable was related to fire history and was derived from the national wildfire database (see section 2.2.1). Specifically, the response variable considered here was a binary classification of patches (burnt patch vs. non burnt patch). To a polygon to be considered as “burnt” it had to comply with at least one of the following two rules: (1) in any of the years of the focal time frame, 50% or more of its area was burnt; or (2) during a focal decade, 70% or more of its area was burnt.

2.3.3.3. Modelling framework: Prolog in the context of machine learning algorithms

One of the main tools used in this study was Prolog. Prolog stands for “PROgramation en LOGic" (Colmerauer *et al.*, 1973), and it was one of the first and is still one of the most popular logic programming languages. It was developed as an attempt to implement Colmerauer and Kowalski's idea of computation as controlled inference (Kowalski, 1974). The goal in Prolog is to separate the specification of what the program should do from how it should be done. In Prolog the user specifies application knowledge (facts and rules) and queries in a declarative way using logic, leaving the problem of how to solve the query using the specified knowledge to the Prolog system.

Machine Learning is the study and development of empirical data based algorithms that allow systems to improve their behaviour over time (Mohri *et al.*, 2012). As an example, suppose we are given a database with fire events occurring in a given region, plus landscape properties such as the distance of each occurrence to water. If the data show that most of the regions far from water have burnt, a typical application of machine learning would infer general rules such as "If a region is far from water, it will burn".

Ideally, observed data would follow an unknown but computable theory *T*. In this case, we could use inductive reasoning to unveil the theory *T* that fully explains the data (Raedt, 2008). In practice, we have limited amount of data, noisy data and we only have a partial understanding of the problem, so we can only approximate *T*.

2.3.3.4. Classification problems

In classification problems the data are split into positive (True) and negative (False) examples. In order to score a theory *T* we must analyse how *T* covers the examples. Three of the most used methods for this purpose are *Confusion Matrix, Accuracy and Precision/Recall.*

A Confusion Matrix is a visual aid formed by two columns representing the actual observations and by two rows representing the predicted results. An example is given in Figure 2.29. A binary classifier will have four cases:

- True Positive (TP), i.e. those correctly labelled as positive; in the example: 4;
- False Positive (FP), i.e. those wrongly labelled as positive; in the example: 1;
- False Negative (FN); i.e. those wrongly labelled as negative; in the example: 2;
- True Negative (TN), i.e. those correctly labelled as negative. In the example: 3.

		Actual		
		+	-	
Pred	+	4	1	5
	-	2	3	5
		6	4	10

(a) Example

		Actual		
		+	-	
Pred	+	TP	FP	TP+FP
	-	FN	TN	FN+TN
		TP+FN = P	FP+TN = N	P+N

(b) Definition

Figure 2.29 Example of confusion matrix with TP (true positives), FP (false positives), FN (false negatives), TN (true negatives). Source: Stehman 1997.

Often one wants a single number to measure the quality of *T*. *Accuracy* gives the percentage of correctly predicted examples (both positive and negative) over all examples:

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Precision/Recall is an alternative metric useful when we have a large number of negative examples (Figure 2.30). This is the case with our data; the wildfire dataset is extremely skewed in the negative (not burnt) side. *Precision* is the percentage of true positives out of all predicted positive examples. A high precision means most of the predicted positive examples are actual positive examples, regardless of whether we miss some (or many) positive examples. *Recall* is the percentage of true positives out of all observed positives examples. A high recall means that most of the positive examples are found, even if we also label many negative examples as positive (Figure 2.30).

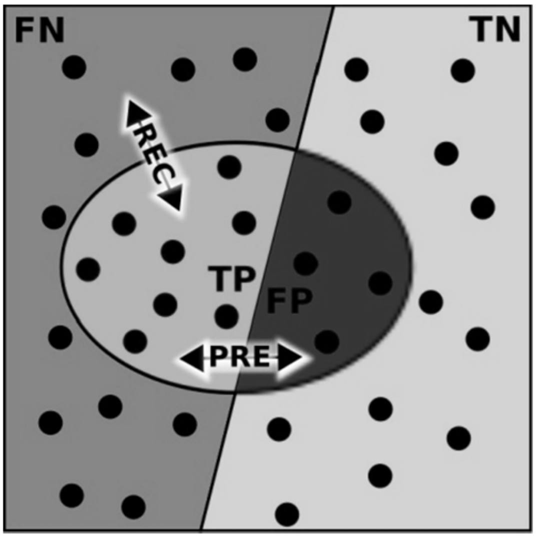


Figure 2.30 Graphic representation of the *Precision/Recall* concept. Precision (PRE) and recall (REC) are the quotient of the light and dark regions, respectively. Precision = TP / (TP + FP). Recall = TP / (TP + FN). Source: Wikipedia (January 2013).

2.3.3.5. Training and testing a rule set

Evaluating a theory based on the training data alone does not guarantee that the theory will perform well with new data. To best score the theory, the data are usually split into training and testing sets. We used as training set the data from a land cover map of year 1990 and the following decade of wildfires (1991-2000), and as test set the data from a land cover map of year 2000 and the following decade of wildfires (2001-2010). These land cover and fire datasets were described in section 2.2.

2.3.3.6. ILP - Inductive Logic Programming

Inductive Logic programming (ILP) is a research area formed at the intersection of Machine Learning and Logic Programming (Muggleton, 1991). Induction, a form of reasoning and the counterpart of deduction, can be seen as learning theory *T* from examples, the same general objective of machine learning. This is in fact a good definition to ILP itself, where the main goal is to derive theories from examples.

As with human reasoning, in ILP we are allowed to use domain knowledge, here known as *background knowledge*, in order to help the system derive better theories.

In ILP, the example set *E*, the background knowledge *B* and the theory itself *T* are all well-formed Prolog programs. Usually we divide *E* into positive examples *E*^+ and negative examples *E*^-, thus *E* = *E*^+ *V E*^-. The objective is to find a hypothesis *H* which explains the positive examples while not explaining the negative examples.

2.3.3.7. Aleph

Aleph (A Learning Engine for Proposing Hypotheses; Srinivasan, 2007) is one of the many ILP systems. We briefly describe the key parameters here.

Aleph allows fine-tuning a set of parameters that control the ILP search. The most relevant to our work are the following:

evalfn (our case auto_m) - Sets the evaluation function for a search.

i (in our case: 3) - Controls the size of the bottom clause, by setting an upper bound on the number of new variables. The larger the *i* the larger the bottom clause will be. So for a very large *i* the system may just spend too much time generating the bottom clause, whereas for very small *i* it may lose interesting clauses.

minacc (in our case: 10%) - Sets a lower bound on the minimum accuracy of an acceptable clause.

minpos (in our case: 20) - Sets a lower bound on the number of positive examples to be covered by an acceptable clause. This is useful to avoid very specify clauses that only cover very few examples.

noise (in our case: 1000) - Sets an upper bound on the number of negative examples allowed to be covered by an acceptable clause. With noisy data sets this allows to have some flexibility in clause generation.

optimize_clauses (in our case: true) - Performs query optimizations (Costa *et al.*, 2003).

search (in our case: heuristic to speedup) - Sets the search strategy, the most commonly used breath first and heuristic.

Our task was to predict whether a given land cover polygon would suffer a fire event in the next decade. We used the ILP system Aleph (Srinivasan, 2007) running under the Prolog system YAP (Costa *et al.*, 2012) to search for burnt areas. As discussed above (see section 2.2.4), we performed this study for the period between years 1991 and 2000, and tested our results using the 2001-2010 decade. The training dataset consisted of 13 968 polygons, 881 being positive examples (land cover polygons with fire occurrence). We used as negative examples the remainder 13 087 polygons in the dataset. The test data set included a total of 28 670 polygons, 3830 of which being positive examples (land cover polygons with fire occurrence). We used as negative examples the remainder 24 840 polygons in the dataset. Both datasets are therefore highly skewed.

After determining the set of rules with the best performance, we tested this rule set using the 2000 land cover (with a different geometry and number of polygons) and the fire history between 2001 and 2010 as the test data set. Since it was possible to determine for each polygon the number of times that it was “caught” by one of this rules, we also computed the “key” polygons in the model for explaining burnt (positive examples) and non-burnt (negative examples) areas, i.e. those with the highest frequencies in the rule set.

2.3.4. Local controls of post-fire vegetation resilience

2.3.4.1. General approach and workflow

The assessment of the local controls of post-fire vegetation resilience in the Baixo Tâmega region, northwest Portugal, was done through the application of Anova Detrended Correspondence Analysis and Analysis of Similarities on vegetation data to analyse the post-fire behaviour of scrublands. The workflow included the following sequential steps:

(1) Construction and implementation of a sample design that allowed to test the effects of fire history and lithology in scrubland resilience (see section 2.2.5);
(2) Collection of in-field data on vegetation and plant community structure; and
(3) Statistical analysis of the collected data.

2.3.4.2. Explanatory variables and sampling design

Three explanatory variables were considered to explain the patterns of post-fire vegetation recovery: two variables related to fire history (Time Since Last Fire - TSLF, and Recurrence - R) and lithology/bedrock type (schist vs. granite).

The sampling strategy was based on these three variables (see section 2.2.5). The 40 sampling sites were selected according to their fire history (TSLF and Recurrence) and to Lithology. Five replicates were randomly selected for each combination of factors. Sampling was therefore based on a full factorial design with three crossed independent factors. The characteristics of the data and the several response variables computed from those data were described in section 2.2.5.

2.3.4.3. Statistical analyses

One-way analysis of variance (ANOVA) performed in SPSS Statistics® 7.0 was used to detect significant differences among sites in terms of the number of woody species. ANOVA´s assumption of homogeneity of variances was tested with Levene's test, and that of normality of the residual distribution checked graphically by normal probability plots.

Detrended Correspondence Analysis (DCA), with detrending by segments and scaling of ordination scores focusing on inter-sample distances, was performed in CANOCO ver. 4.5 (Braak and Šmilauer, 2002) in order to clarify the relationships among sampling sites based on their floristic composition.

Analysis of similarities (ANOSIM) in PRIMER software (Clarke and Warwick, 2001), based on a Bray-Curtis similarity matrix (Bray and Curtis 1957), was used to test for differences in community structure as a function of TSLF, Recurrence and Lithology and their interactions. ANOSIM calculates a global R statistic that reflects the differences in variability between groups as compared to within groups (so R values are proportional to differences between the groups) and checks for the significance of R using permutation tests (Clarke and Warwick, 2001). Given the differences in community composition between Granite and

Schist and the non-availability of a three-way ANOSIM in the PRIMER software, data were analysed by a two-way ANOSIM with Recurrence and TSLF for each Lithology type.

3. Results

3.1. National patterns and drivers of wildfire occurrence

3.1.1. Rationale and specific objectives

Environmental and ecological systems are complex and dynamic, and therefore difficult to model with standard modelling tools that often are too restrictive in their data distribution assumptions (Elith and Graham, 2009). Several machine learning modelling tools provide sophisticated approaches with less stringent assumptions. Therefore this type of tools has been receiving increasing attention from the environmental and ecological research communities (e.g. Fielding, 1999; Crisci *et al.* 2012).

The nature of the problem being tackled in this study of wildfire patterns and drivers and the properties of the available data require this type of approaches, namely several "state of the art" machine learning tools like Random Forests (Breiman 2001) or Support Vector Machines (Vapnik 1995). Here we use the latter to uncover the key drivers of recent fire history across different regions of continental Portugal. Our underlying rationale was that, in environmentally and socioeconomically heterogeneous countries such as Portugal, the key features of fire regimes will be driven by distinct factors, according to the specific environmental and socioeconomic setting of each region.

3.1.2. Description and interpretation of results

3.1.2.1. Modelling wildfire patterns in Portugal with SVMs

When using the whole country as test area to model wildfire patterns, the best results (i.e. lowest NMAD values) were obtained using the whole set of variables, with NMAD reaching values below 0.6 (Figure 3.1). The Landscape block of variables had the best individual performance whereas the Socio-Economic block achieved the poorest result. The Climate and Topography blocks of variables yielded comparable and intermediate scores.

When analysed separately for the seven agrarian regions of continental Portugal, models using all variables performed better in the northern regions that in the southern regions of the country (Figure 3.2). The "Entre-Douro-e-Minho" (EDM), in the northwest end of the country, was the region with the best performance overall (NMAD=0.55), even better than the performance achieved by the national model.

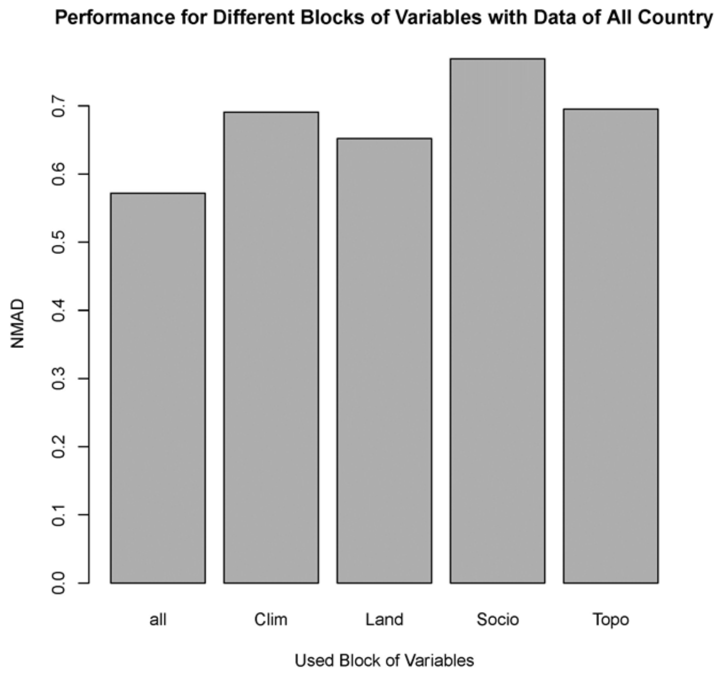


Figure 3.1 Performance of SVMs in explaining wildfire patterns in continental Portugal (whole country), based on the complete set of variables ("all") and on individual blocks of variables (Climate, Landscape, Socio-Economic, and Topography).

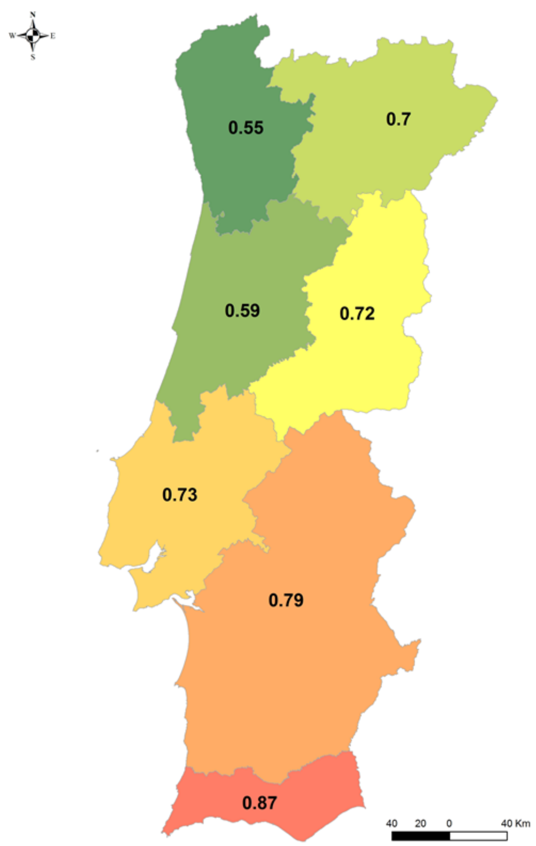


Figure 3.2 Performance (NMAD values) of the SVM models for the several agrarian regions of continental Portugal.

The proportion of the area that burnt in each of the seven regions during the focal time frame was very distinct (Table 3.1), which may have been one of the causes of the asymmetric performance exhibited by the algorithm. In fact, the four northern regions (EDM, TM, BL, BI) had higher fire recurrence and more than 15% of their territory burnt in the time frame considered (1991 to 2000), and many of their parishes had a large proportion of their area affected by fire in the same period (Table 3.1).

Table 3.1 NMAD of SVM models per region and for the whole continental Portugal, against selected fire statistics.

Region	NMAD	mean burnt proportion (%)	mean fire recurrence	standard deviation fire recurrence	proportion of parishes with more than10% burnt area
[EDM] Entre Douro e Minho	0.55	17	2.01	1.22	46.95
[TM] Trás-os-Montes	0.70	18	2.10	1.08	54.94
[BL] Beira Litoral	0.59	16	1.41	1.06	39.81
[BI] Beira Interior	0.72	22	2.08	0.94	72.03
[RO] Ribatejo e Oeste	0.73	4	0.85	0.73	8.80
[ALT] Alentejo	0.79	1	0.79	0.55	1.69
[ALG] Algarve	0.87	6	1.11	0.83	7.32
Whole country	0.57	11	1.44	1.07	42.64

3.1.2.2. Drivers of wildfire patterns across regions in Portugal

Even if relatively small in size, continental Portugal has a large diversity of climatic, topographic, socio-economic and landscape factors (see Methods, section 2.2.1). Considering that fire regimes are also strikingly different across the country (see Table 3.1), our next question was whether the response of fire history to the several types of factors was regionally stratified. We addressed this goal by comparing the performance of models including only a given group of variables with the performance of models including the whole set of variables, for the whole country and for each region (Table 3.2, Figure 3.3 and Figure 3.4). The underlying questions were (1) whether one or more groups of variables would individually outperform using all the data to explain wildfire patterns, and (2) whether such group(s) of variables would differ among regions.

Table 3.2 Performance ranks of the individual blocks of variables and the complete dataset ("all") in explaining wildfire patterns in the whole country and in the different agrarian regions of Portugal.

Rank	Country	EDM	TM	BL	BI	RO	ALT	ALG
1	all	all	all	all	all	Socio	Topo	Topo
2	Land	Land	Land	Topo	Land	Topo	Socio	Clim
3	Clim	Topo	Clim	Land	Topo	Clim	Clim	Land
4	Topo	Clim	Topo	Clim	Clim	Land	Land	Socio
5	Socio	Socio	Socio	Socio	Socio	all	all	all

These analyses revealed that there are differences in the relative effects of the several types of factors across regions (Table 3.2) and that the country is clearly divided in two parts regarding the drivers of wildfire regimes: (1) a northern half in which fire patterns are better explained by multiple factors (i.e. when using the whole set of variables), and (2) a southern half where models based on the whole set of variables were the ones with the lowest performance (Figure 3.3).

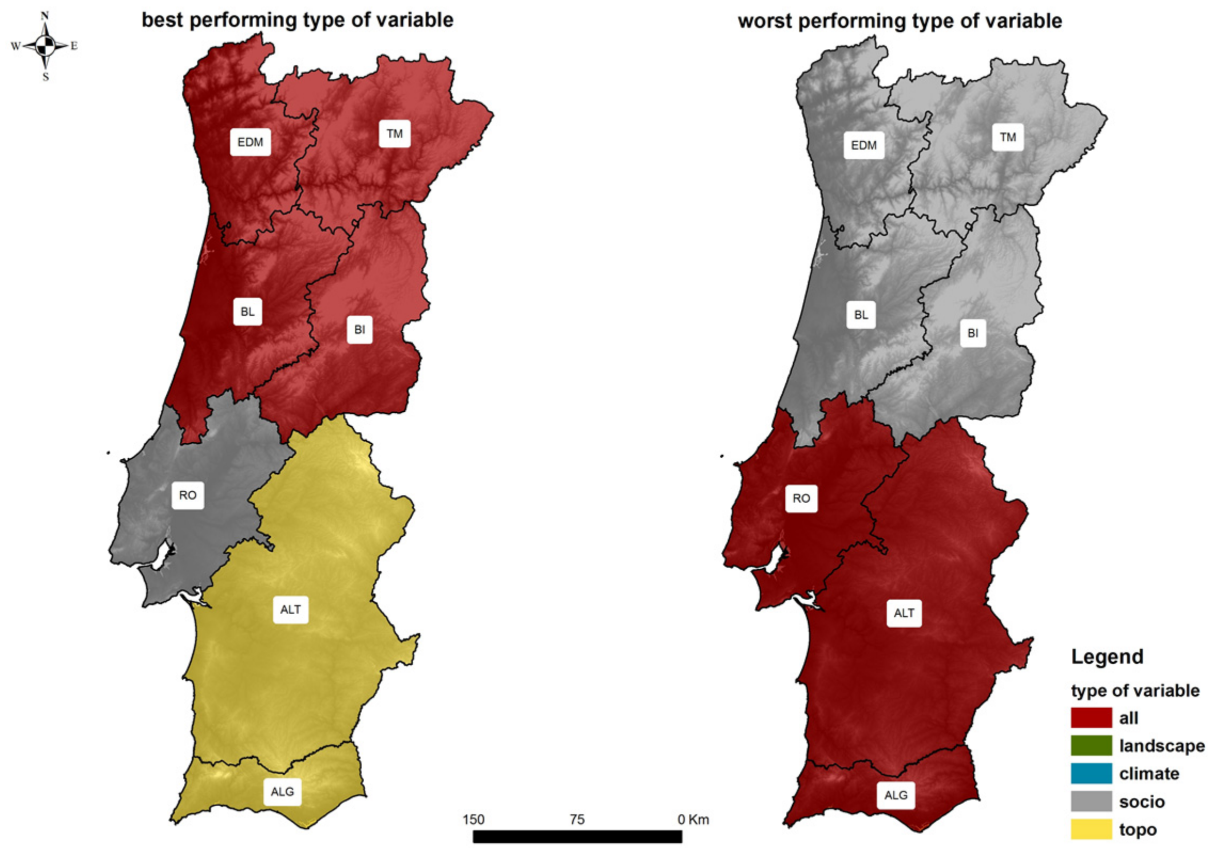


Figure 3.3 Best performing (left) and worst performing (right) blocks of variables in each of the seven agrarian regions of Portugal.

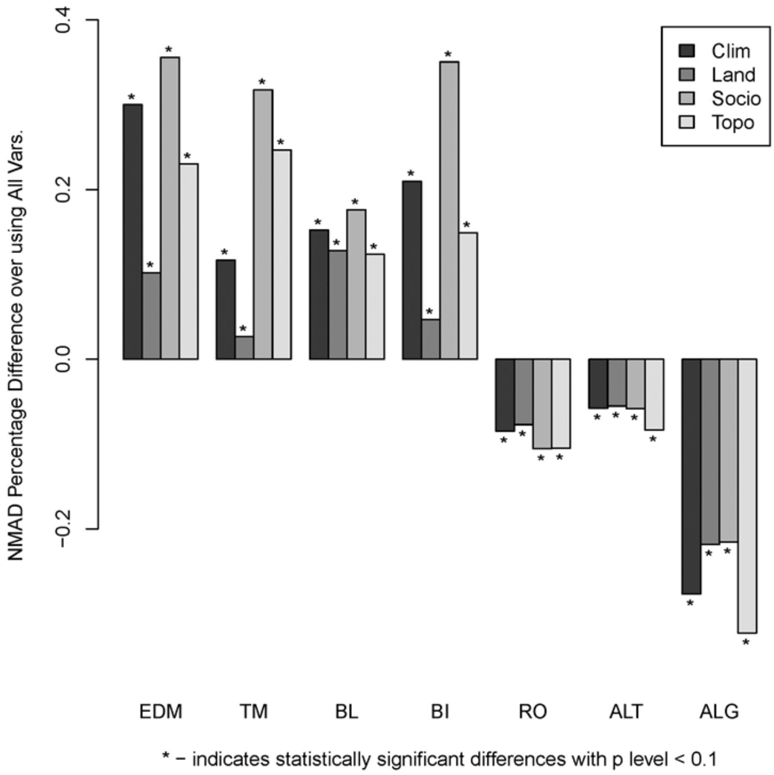


Figure 3.4 Differences (and statistical significance) of NMAD for the seven agrarian regions compared to using all country data, when testing the effects of all types of variables or of individual types of variables on fire regime. Positive values in the vertical axis signal worse performance in individual regions compared to the whole country for a given set of variables.

In the northern part of the country, the Landscape group was usually the one exhibiting lower loss in model performance when compared with using he whole dataset (Table 3.2, Figure 3.4). Also, all differences between the performance of each block of variables compared with that attained by that block for the whole country are statistically significant (Figure 3.4). Overall, these results suggest that the drivers of fire history in Portugal must be analysed separately per region

3.1.2.3. Individual performance of the several groups of variables across regions

The final goal was to compare the individual performance of the several groups of variables in each region (Figure 3.5).

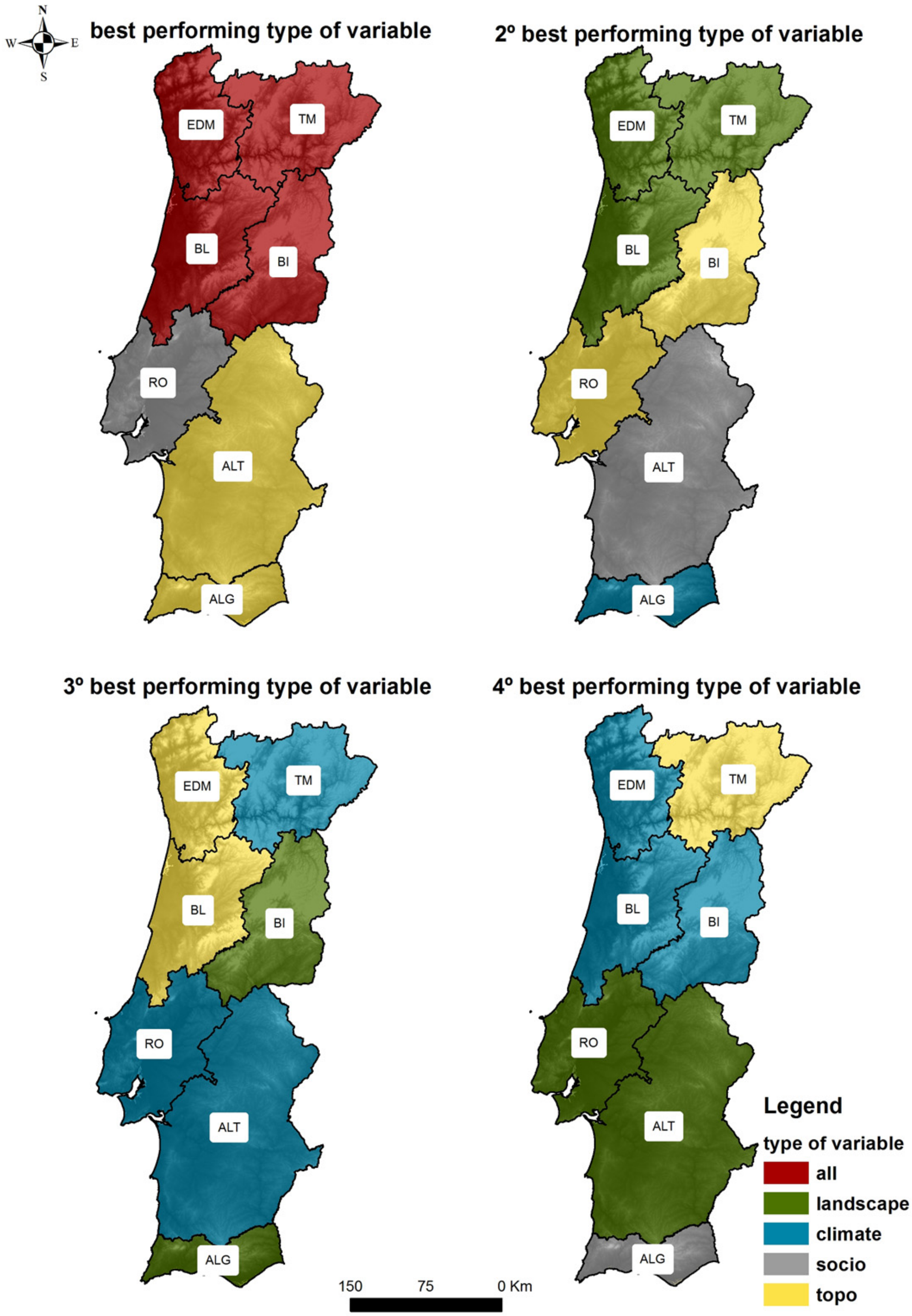


Figure 3.5 Ranking of variable blocks and of the whole dataset in the seven agrarian regions of Portugal.

Analysing the main results contained in Table 3.2 geographically highlights the strong variations in the relative importance of variable blocks to explain fire patterns across regions. Individually, landscape variables represent the most important block in most of the northern regions (it is however of lesser importance towards south; Figure 3.5). The statistical tests presented in Figure 3.6 further highlight the importance of the Landscape block to explain fire patterns in the northern part of the country.

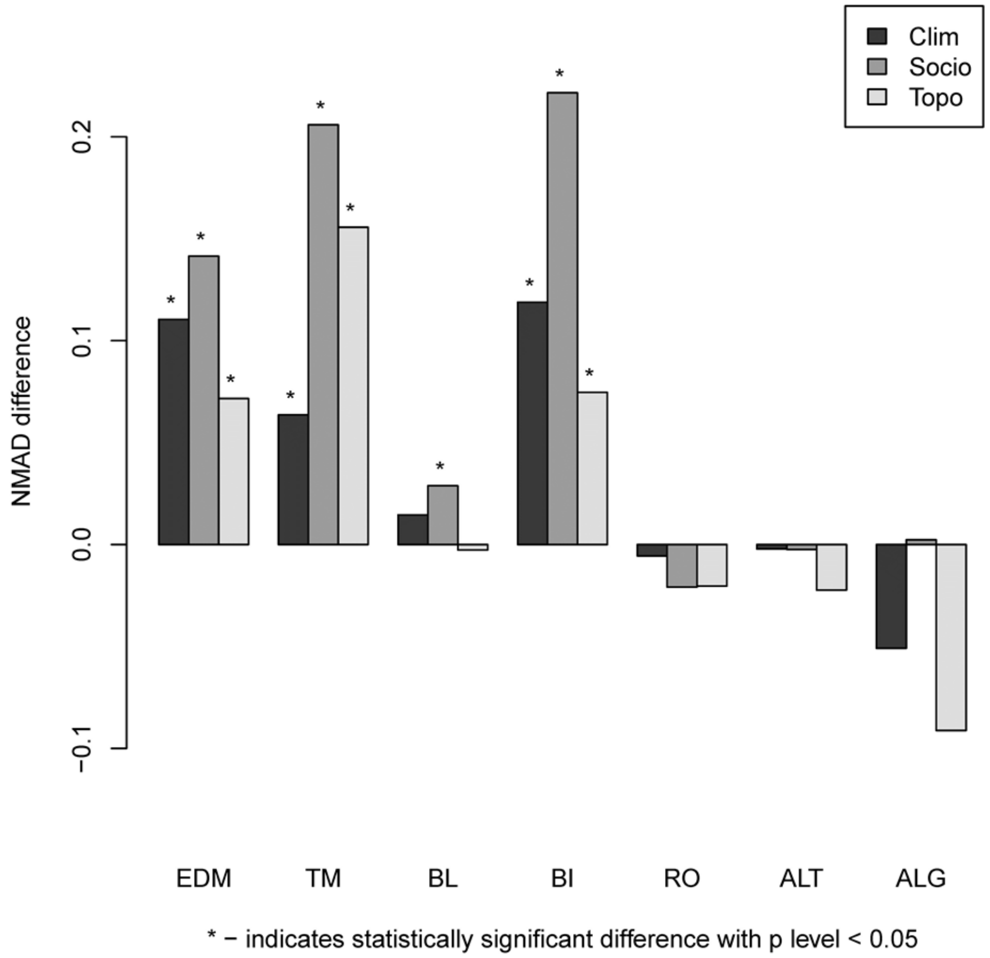


Figure 3.6 Difference of NMAD between using only the Landscape block and using any of the other blocks of variables individually. Positive values in the vertical axis represent cases in which using the Landscape block alone yields lower values of NMAD (i.e. better performance) that the other block of variable being compared.

Conversely, topography and socio-economy seem to be the most important effects in the southern part of the country, whereas they are of less importance to explain fire patterns towards north (Figure 3.5). Climate, on the other hand, is only the second best performing block in ALG, thus apparently representing the least important block overall.

3.2. Regional patterns and drivers of wildfire occurrence

3.2.1. Rationale and specific objectives

Fire regimes in environmentally and social-ecologically heterogeneous regions are influenced by many different factors. As described in the Introduction (see section 1.3), environmental drivers such as climate or topography, socioeconomic factors such as demography or land uses, and mixed factors such as land cover and landscape structure, jointly contribute to shape regional fire history (Marques *et al.*, 2011; see also section 3.1).

Since these factors may influence fire occurrence (ignition and/or spread) at different scales of space and time (Ganteaume *et al.*, 2013), and due to the many possible interactions among drivers (Miranda *et al.*, 2012), the resulting wildfire patterns are often rather complex and therefore difficult to explain and/or predict. In this context, robust modelling frameworks can be rather useful to identify general wildfire patterns as well as to discriminate their underlying determinants.

Here we explored the potential of inductive logical programming (ILP; Vaz *et al.*, 2007) to extract a general rule set that could successfully explain the spatial patterns of wildfire events that occurred during the 1990s in the Alto Minho, a heavily burnt, heterogeneous region in northwest Portugal. Such rule set was then tested against an independent wildfire dataset (burnt areas in the 2001-2010 time frame). The rationale of this modelling framework as well as the workflow were described in detail in the Methods section (see 2.3.3).

3.2.2. Description and interpretation of results

3.2.2.1. Rule set performance

A rule set consisting of 15 rules was generated by the ILP algorithm to explain the patterns of wildfires in the Alto Minho (1991-2000 time frame). When tested against the training dataset (as described in the Methods section; see 2.3.3), the performance of this rule set can be described as follows (Table 3.3):

- From the 881 burnt polygons in the dataset, 731 polygons corresponded to true positive (TP) cases (i.e. correctly labelled as burnt), and 150 polygons corresponded to false positive (FP) cases (i.e. wrongly labelled as burnt);

- From the 13 087 unburned polygons in the dataset, the number of false negative (FN) cases (i.e. wrongly labelled as unburned) was 3971, and the true negative (TN) cases (i.e. correctly labelled as unburned) was 9116.

Table 3.3 Confusion matrix describing the success of the rule set in predicting burnt patches in the training dataset (1991-2000).

	Observed		
Predicted	**+**	**-**	**Total**
+	731	3971	4702
-	150	9116	9266
Total	881	13 087	13 968

When tested against the training data, the rule set thus exhibited an Accuracy (i.e. the fraction/percentage of all cases that corresponds to correctly predicted cases, both positive and negative) of 0.71 (71%), which can be considered a good performance (Vaz *et al.*, 2011). This high value is mostly influenced by the high total number of true negative cases (due to the expected negative bias of the wildfire database; Table 3.3).

In cases like wildfire datasets, which are usually rather skewed towards the negative (not burnt) side of the distribution, measures like Precision and Recall can be very useful (see section 2.3.3). In this test against the training dataset, our rule set achieved a Recall (i.e. the fraction/percentage of true positives out of all positives examples) of 0.83 (83%), meaning that most of the positive examples (i.e. actually burnt polygons) were predicted by the rule set. On the other hand, Precision (i.e. the fraction/percentage of true positives out of all predicted positive examples) was only 0.2 (20%), expressing the fact that many cases predicted as burnt actually corresponded to unburned polygons (i.e. false positives). These results become clear in the spatial expression of Recall and Precision of the rule set against the training data (Figure 3.7).

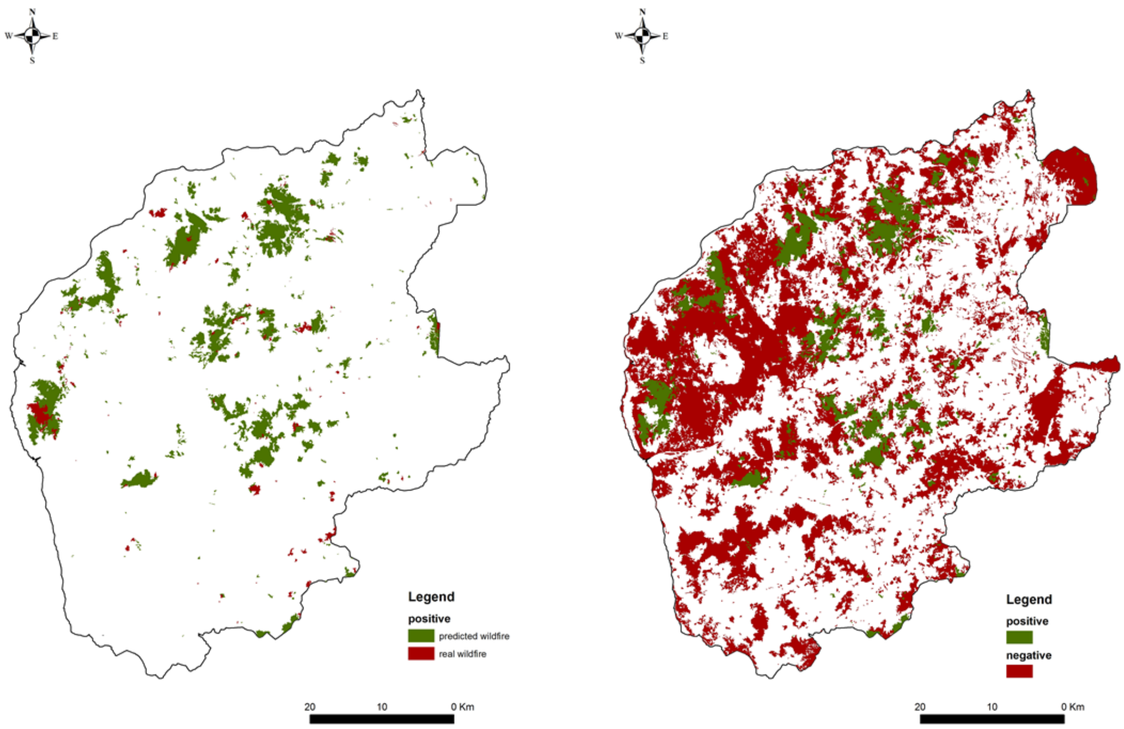


Figure 3.7 Spatial expression of performance statistics of the rule set against the training data: (left) Recall: only the actually burnt polygons are represented, with those correctly classified by the algorithm overlapping in green; (right) Precision: all polygons predicted as positive (i.e. burnt) by the rule set are represented, with the true positive (i.e. correctly predicted as burnt) overlapping in green.

The test dataset was based on a new land cover map (from year 2000) and the fire records of the decade 2001-2010. Since the geometry and number of polygons are different and the burnt polygons were calculated using a different time frame, this test set can be considered independent from the training set. The test set performance (Table 3.4) follows the same pattern as the training set, with a slightly worst performance in Recall (0.69, or 69%) and a better performance in Precision (0.28, or 28%). The overall Accuracy was 0.72 (72%).

Table 3.4 Confusion matrix describing the success of the rule set in predicting burnt patches in the test dataset (2001-2010).

	Observed		
Predicted	**+**	**-**	**Total**
+	2638	6969	9607
-	1192	17871	19063
Total	3830	24840	28670

The spatial expression of Recall and Precision of the rule set against the test data is depicted in Figure 3.8. To test whether the good Recall achieved for the test dataset was not spuriously influenced by the increase in the total number of polygons (when compared with the training dataset), we performed a Fisher's Exact Test (with a 95% confidence interval). The test rejected (p-value < 2.2e-16) the null hypotheses that the model does not perform better than a random selection of polygons. The rule set thus proved to be successful in predicting wildfires on an independent dataset.

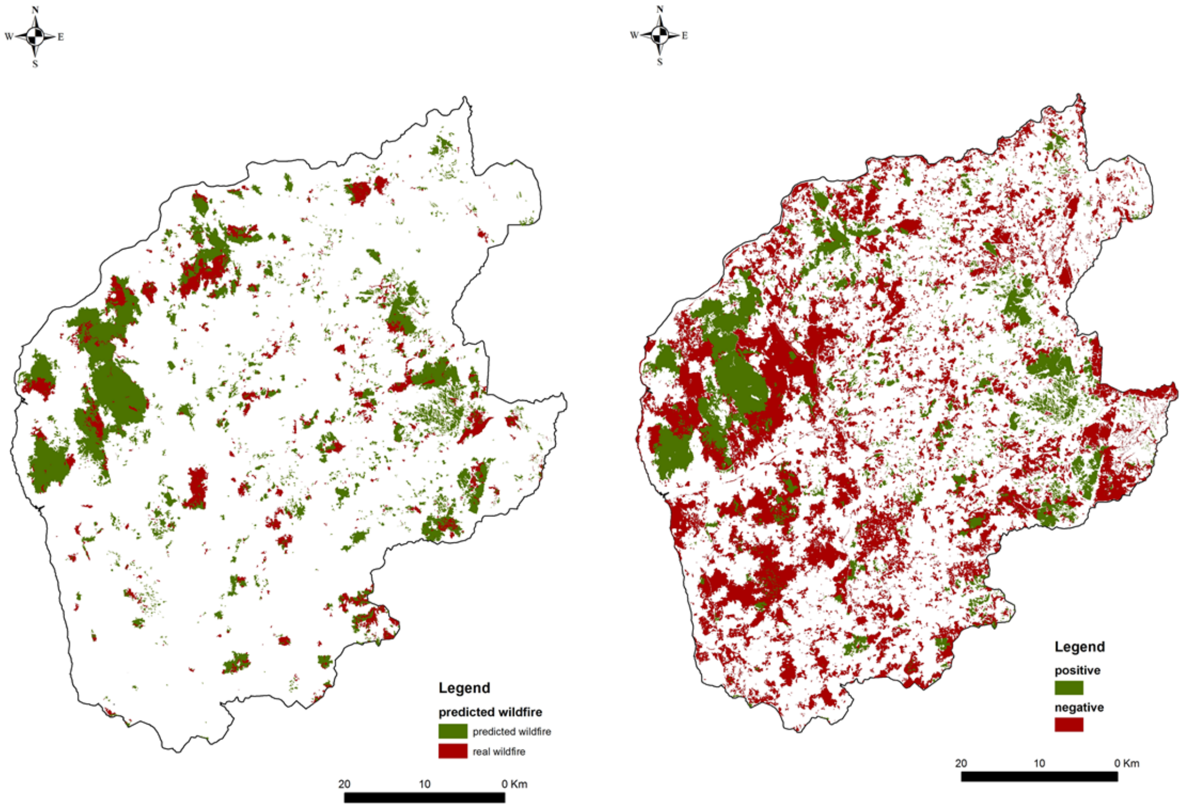


Figure 3.8 Spatial expression of performance statistics of the rule set against the test data: (left) Recall: only the actually burnt polygons are represented, with those correctly classified by the algorithm overlapping in green; (right) Precision: all polygons predicted as positive (i.e. burnt) by the rule set are represented, with the true positive (i.e. correctly predicted as burnt) overlapping in green.

3.2.2.2. Analysis on individual rules and polygons

Table 3.5 provides a summary of the number of polygons in the training dataset covered by the several rules in the study area. Any given rule applies to a minimum of 1.2% of all polygons, but no single rule covers more than 6.5% of all polygons, for an overall mean of 2.4%. The rule set covers 35.5% (4957) of a total of 13 968 land cover polygons in the test area. On average, a given rule achieved a Precision of 18.5% (i.e. 18.% of polygons covered by that rule corresponded to positive cases, i.e. burnt areas), with values ranging between a minimum of 10.5% (rule n. 15) and a maximum of 24.7% (rule n. 14).

Table 3.5 Summary statistics for the set of 15 rules applied to the training dataset. Note that a given patch/polygon may have been classified as positive by more than one rule.

Rule n.	Total N. of polygons covered by the rule	% of total N. of patches	Positive polygons		Negative polygons	
			N	% of rule patches	N	% of rule patches
1	914	6.5	170	18.6	744	81.4
2	162	1.2	22	13.6	140	86.4
3	305	2.2	73	23.9	232	76.1
4	561	4.0	104	18.5	457	81.5
5	407	2.9	80	19.7	327	80.3
6	591	4.2	92	15.6	499	84.4
7	162	1.2	26	16.0	136	84.0
8	168	1.2	33	19.6	135	80.4
9	294	2.1	64	21.8	230	78.2
10	233	1.7	28	12.0	205	88.0
11	248	1.8	36	14.5	212	85.5
12	249	1.8	60	24.1	189	75.9
13	210	1.5	46	21.9	164	78.1
14	243	1.7	60	24.7	183	75.3
15	210	1.5	22	10.5	188	89.5
Rule set	4957	35.5	916	18.5	4041	81.5

We selected two rules among those with the highest values of Precision (n. 3 and n. 14; see Table 3.5) from the rule set for a more detailed analysis. These two rules differ in the number of factors used in their formulation and so in their complexity. They are described below (Table 3.6 and Table 3.7) regarding their logical formulation (i.e. the native formulation of the rule), their ecological translation (i.e. a direct translation of the logical formulation), their spatial expression (i.e. distribution in the test region), and their ecological interpretation (i.e. a description of the ecological and spatial attributes of the rule).

Since some polygons may have been classified by more than one rule, analysing the number of rules that cover a given polygon can provide some indication of its relative importance in the construction of the rule set and therefore in the explanation of recent fire history in the study area. Figure 3.9 describes the result of this analysis for both the training and test datasets.

Table 3.6 General description of Rule n. 3 from the rule set generated to explain wildfire occurrence in the Alto Minho (1991-2000).

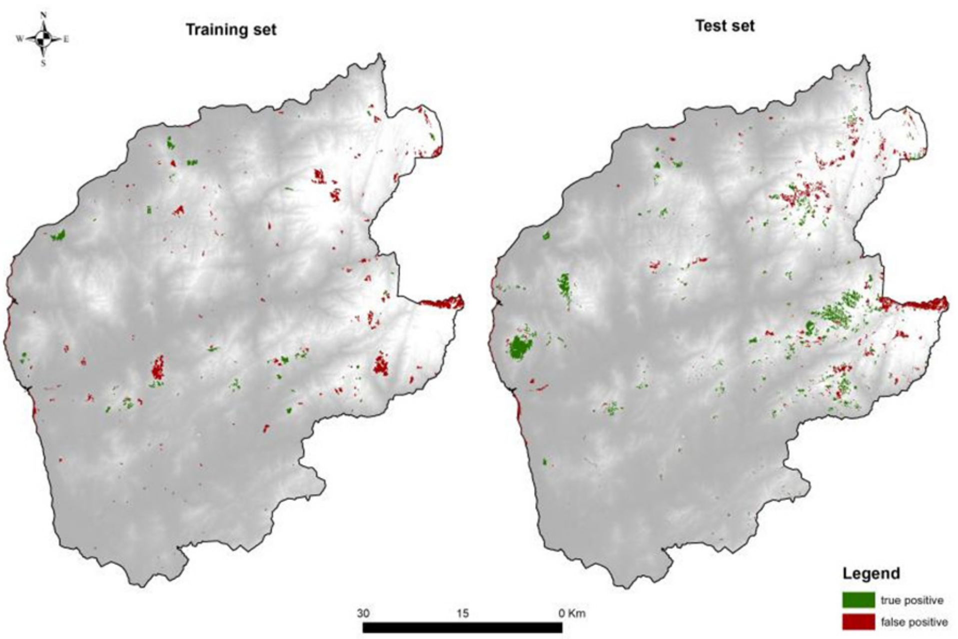
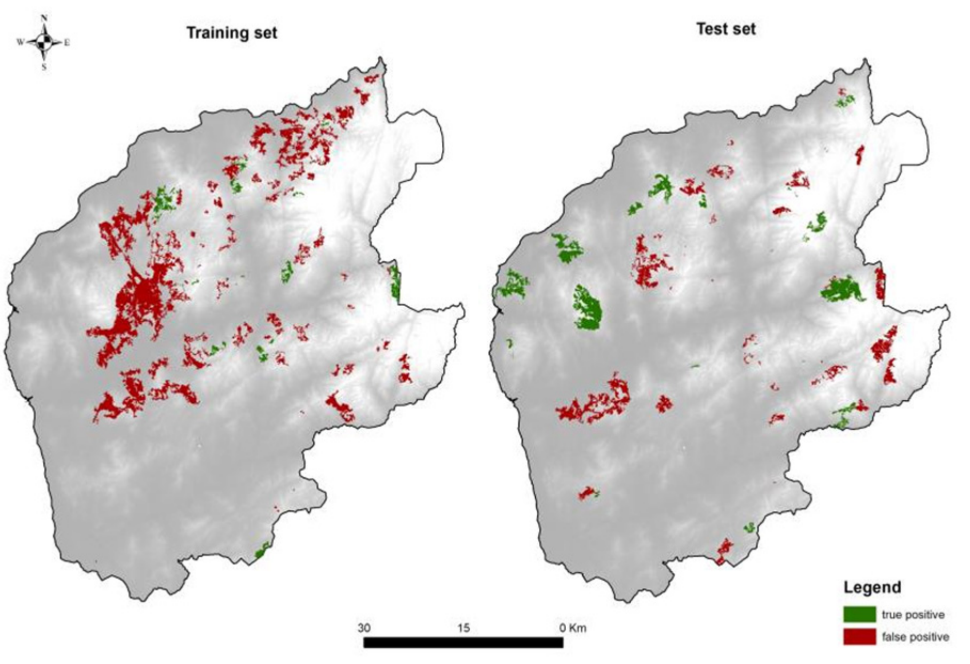
Logical formulation	% [Rule 3] [Pos cover = 73 Neg cover = 232] burnt(A) :- terrain(A,sparse_vegetation,jy,granite_and_related_rock_types,_,_,_,_,_,_,_,_).
Ecological translation	Rule 3 covers: • 73 patches/polygons affected by fire and 232 not affected by fire in the training dataset, • 632 patches/polygons affected by fire and 445 not affected by fire in the test dataset. The focal patch (A): • corresponds to land cover classes ‘sparse vegetation’ or ‘rock outcrop’, • occurs in areas where lithology is granite and related bedrock types.
Spatial expression	
Ecological interpretation	The land cover patches (polygons) covered by this rule are included in sparsely vegetated areas with granitic bedrock. These patches are located at various elevations, aspects and slopes, occurring scattered in the region but particularly towards the eastern mountain areas (particularly in the test dataset).

Table 3.7 General description of Rule n. 14 from the rule set generated to explain wildfire occurrence in the Alto Minho (1991-2000).

<table>
<tr><td>Logical formulation</td><td>% [Rule 14] [Pos cover = 60 Neg cover = 183]
burnt(A) :-
class(A,p), neighbour(A,B), terrain(B,shrubland,ii,granite_and_related_rock_types,C,E,D,_,_,_,_,_),
geq(C,305.557), geq(D,0.464287), geq(E,17.4567).</td></tr>
<tr><td>Ecological translation</td><td>Rule 14 covers:
• 60 patches/polygons affected by fire and 183 not affected by fire in the training dataset,
• 42 patches/polygons affected by fire and 138 not affected by fire in the test dataset.

The focal patch (A):
• corresponds to land cover class ‘pine forest’,
• neighbours patch of land cover class ‘shrubland’, on granite and related rock types, at a mean altitude ≤ 305.5 m a.s.l., with a slope ≤ 0.47 and eastness ≤ 0.175.</td></tr>
<tr><td>Spatial expression</td><td>
</td></tr>
<tr><td>Ecological interpretation</td><td>The land cover patches (polygons) covered by this rule are included in forest landscapes with presence of pine stands and scrub, on granitic soils. These patches are located at low elevations and various aspects (except east), somewhat concentrated in the catchments of rivers Minho and Lima.</td></tr>
</table>

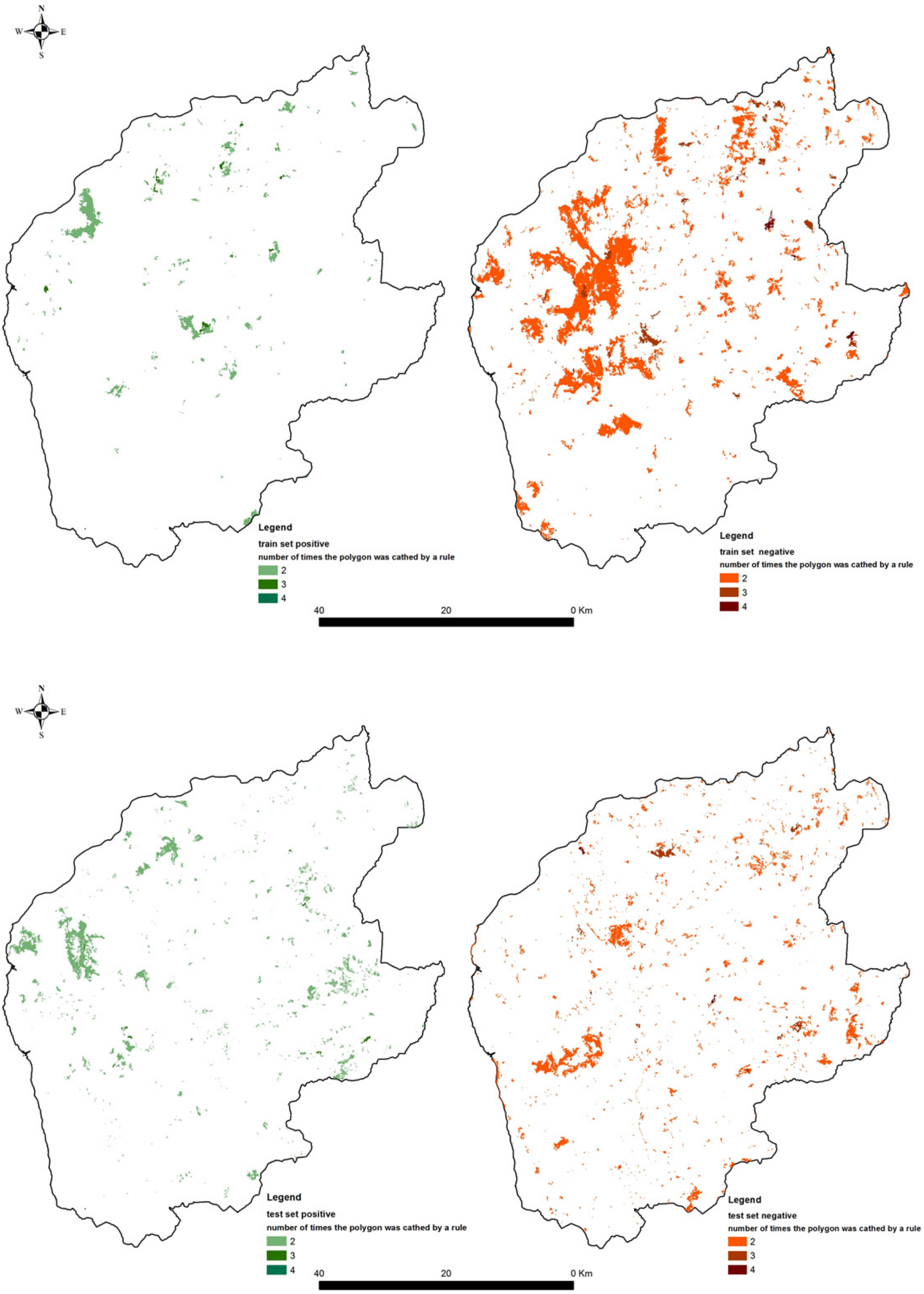


Figure 3.9 Frequencies of individual polygons in the whole rule set, for the training dataset (top) and for the test dataset (bottom). Maps on the left represent actually burnt polygons (true positive cases) and maps on the right represent polygons that were incorrectly classified as burnt (false positive cases).

3.2.2.3. Frequencies of wildfire factors in the rule set

A simple analysis of the frequencies of the environmental several factors across the rule set (Table 3.8) reveals that land cover (namely the presence of forests, scrubland or sparse vegetation over the landscape) and lithological class (bedrock type) were the most important factors overall to explain the patterns of wildfire occurrence in the study area.

Table 3.8 Importance of the several types of factors, measured from their frequency across the rule set. The presence/neighborhood of forest and/or scrub and the type of bedrock were the most frequent factors across the rule set (highlighted in bold characters). The five rules with the highest individual Precision values are highlighted in grey.

Types of factors	Factors	Rule n.															N
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	
Climate	Temperature																0
	Precipitation																0
Topography	Altitude														x	x	2
	Slope					x									x		2
	Aspect														x		1
Land cover	**Forests**		**x**			**x**	**x**	**x**	**x**		**x**	**x**	**x**	**x**	**x**	**x**	**11**
	Scrubland	**x**			**x**		**x**			**x**	**x**				**x**		**6**
	Agricultural land													x		x	2
	Sparse vegetation			x					x					x	x		4
	Artificial areas																0
Area	Patch area																0
Distances	To rivers																0
	To roads																0
Lithology	**Lithological class**	**x**		**x**	**x**	**x**						**x**	**x**		**x**	**x**	**8**
Soil	Soil class									x							1
Socio-economic	Demographic and livestock											x					1

All other factors achieved very low frequencies or were even absent from the rule set. Nonetheless, the five rules with the highest individual Precision values (see 3.2.2.2), highlighted in Table 3.8, were largely based on distinct sets of factors as well as on different numbers of factors, with a minimum of two factors in rules n. 3, 9 and 12, and a maximum of seven factors in rule n. 14.

3.3. Regional patterns and drivers of post-fire resilience

3.3.1. Rationale and specific objectives

The spatiotemporal variability of climate conditions and the heterogeneity in vegetation and fuel load play an essential role in determining fire behaviour and severity across the landscape. However, most studies on fire ecology are focused on the relationship between wildfire patterns and the structural features of the landscape, like land cover categories (Stolle *et al.*, 2003; Nunes *et al.*, 2005; Bajocco and Ricotta, 2008) and vegetation types (Cumming, 2001; Pezzatti *et al.*, 2009), while the functional characteristics of the landscape, like land degradation, vegetation productivity or fuel phenology, are only rarely considered (but see De Angelis *et al.*, 2012).

However, in areas with Mediterranean type of climate, the high seasonality of wildfire occurrence, with a concentration of events during the dry and hot summer months (Keeley and Fotheringham, 2003; Pausas, 2004; Bajocco and Ricotta, 2008), and the strong relation between the seasonal timing of vegetation (the major source of fuel) and the associated wildfire regimes (Bajocco *et al.*, 2010), suggest that looking at the functional characteristics of the landscape allows adding a dynamic component to the analysis of fire patterns and impacts. This functional approach is rather useful when dealing with global change issues and when predicting future fire behaviour under different environmental scenarios (Bajocco *et al.*, 2010a). In this regard, vegetation phenology (i.e., the timing of plant development stages, most often under the influence of climatic seasonality) plays an important role in supporting fire studies (Bajocco *et al.*, 2010a; Akther and Hassan, 2011).

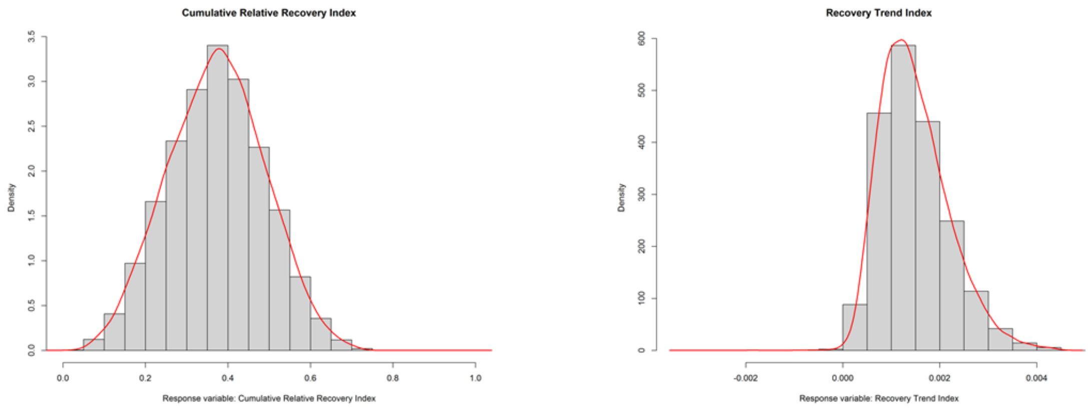
As vegetation phenological status represents the primary driver influencing fuel characteristics, in terms of both fuel availability and moisture content (De Angelis *et al.*, 2012), any investigation on fire monitoring and prediction over large areas requires the capability of capturing broad-scale changes in vegetation phenology that are descriptive of changes in fuel conditions. Remotely sensed observations derived by sensors like MODIS meet these requirements since they provide comprehensive spatial coverage (from 250m to 1km of pixel size) and enough temporal resolution (16-days composites of daily images) to update fuel conditions in a more efficient and operational manner than traditional aerial photography (Oswald *et al.*, 1999) or fieldwork (Riano *et al.*, 2002). Furthermore they have been particularly useful for investigations of wildfire history (Hicke *et al.*, 2003), fuel load production (Roberts *et al.*, 2003), and impact of land use on fuel load (Bachelet *et al.*, 2000).

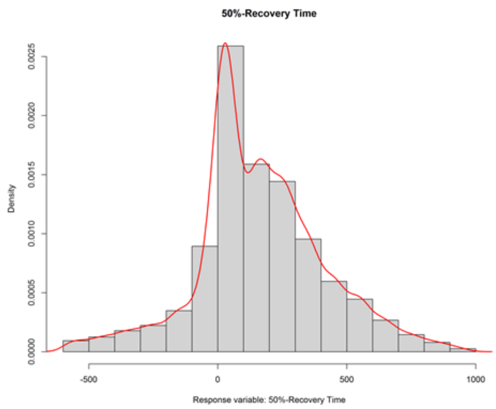
Here we explored the usefulness of high-temporal resolution satellite products (from the MODIS sensor) to assess post-fire vegetation dynamics (i.e. regeneration) and to identify its main drivers at the regional scale in the North of Portugal. Using a limited set of regeneration indicators, we first analysed pre- and post-fire NDVI profiles of a set of areas burnt in a focal year (2005). Then we analysed the patterns of those indicators using the Random Forest (RF) algorithm (Breiman, 2001) implemented in R's *randomForest* package (Liaw and Wiener, 2002), as described in section 2.3.2. Finally, we explore in more detail the effect of the main factors identified by our models on post-fire regeneration.

3.3.2. Description and interpretation of results

3.3.2.1. Regional patterns of post fire recovery

The statistical distributions of the three post-fire regeneration indicators used in this study are illustrated in Figure 3.10, for areas of the study region that were burnt in year 2005.





	Min.	1st Quantile	Median	Mean	3rd Quantile	Max.
CRRI (unitless)	0	0.290	0.373	0.372	0.452	0.986
RTI (year^{-1})	0.0745	0.0221	0.0315	0.0340	0.0435	0.1060
50%RT (days)	-593	19	144	164	312	965

Figure 3.10 Histograms of distribution frequencies for the cumulative relative recovery index (CRRI) (top left), the recovery trend index (RTI) (top right), and the 50 % recovery time (50%RT) (bottom left); and corresponding main descriptive statistics (bottom right).

The cumulative relative recovery index (hereafter CRRI) shows a distribution close to Normal, with a quite symmetric distribution curve. The recovery trend index (hereafter RTI) also shows a distribution curve close to Normal, but with less symmetry and higher prevalence of values close to the mean, evidencing a leptokurtic shape. Conversely, the 50% recovery time (hereafter 50%RT) presents the more asymmetrical and far for Normal distribution curve, with many values concentrated in the immediate post-fire year and a pronounced decreasing trend afterwards. The negative values of this variable correspond to projected values of the 50%RT for a period before the beginning of year 2006, since the values for this variable were extrapolated from the recovery curve, as described in the methods section (see 2.3.2).

Figure 3.11 illustrates examples of NDVI anomalies obtained for each of the three post-fire regeneration indicators, for three selected pixels corresponding to the 25, 50 and 75% quantiles of the regional distribution of the indicators (see Figure 3.10). These pixels represent, for each of the indicators, the regional variations of post-fire regeneration, from those areas showing low and/or slow regeneration capacity to those exhibiting high and/or fast regeneration ability.

Moreover, the NDVI anomalies depicted in Figure 3.11 reveal a general tendency for an increase of the inter-annual range of their photosynthetic activity (related to climatic seasonality), suggesting a higher dependence of suitable environmental conditions in early post-fire regeneration and/or a shift towards different, early successional vegetation types.

The spatial patterns illustrated in Figure 3.12 reveal that local variations, rather than regional patterning, are the most common for all three indicators, suggesting a prevailing role for local landscape controls, rather than regional climatic effects, on the post-fire regeneration process. This is particularly evident for medium to large sized fires. Conversely, small sized burnt areas seem to be characterized by predominantly low regeneration values (Figure 3.12). To further explore the effect of fire event area, we performed a cross-tabulation of the three response variables and of the break magnitude index (a proxy indicator of intensity/severity of the fire event) against burnt patch area (Table 3.9).

Smaller burnt patches tend to exhibit higher break magnitude values, and thus higher fire damage/severity, and lower post-fire recovery ability (as portrayed by RTI and by CRRI; Table 3.9). Nevertheless, our results also show that these small fires lead to faster short-time recovery, observable in the 50%RT indicator (median equal to 55 days, well below the time required for medium and large sized fires). These results seem to suggest strong differences (and thus complementarity) between recovery time (50%RT) and the two other indicators (CRRI and RTI) in assessing post-fire regeneration processes, since they are probably characterizing short and long-term vegetation recovery, respectively. This is also confirmed by the low correlation values between these variables (see Table 2.11). No significant differences (using Wilcoxon signed-rank tests) were observed for pre-fire median NDVI values between each area-quantile ($NDVI_{Q25\%}$ = 0.68, $NDVI_{Q50\%}$ = 0.70, $NDVI_{Q75\%}$ = 0.69) and the whole study area ($NDVI_{all}$ = 0.69), excluding a possible effect of pre-fire conditions on the differences observed among area-quantiles.

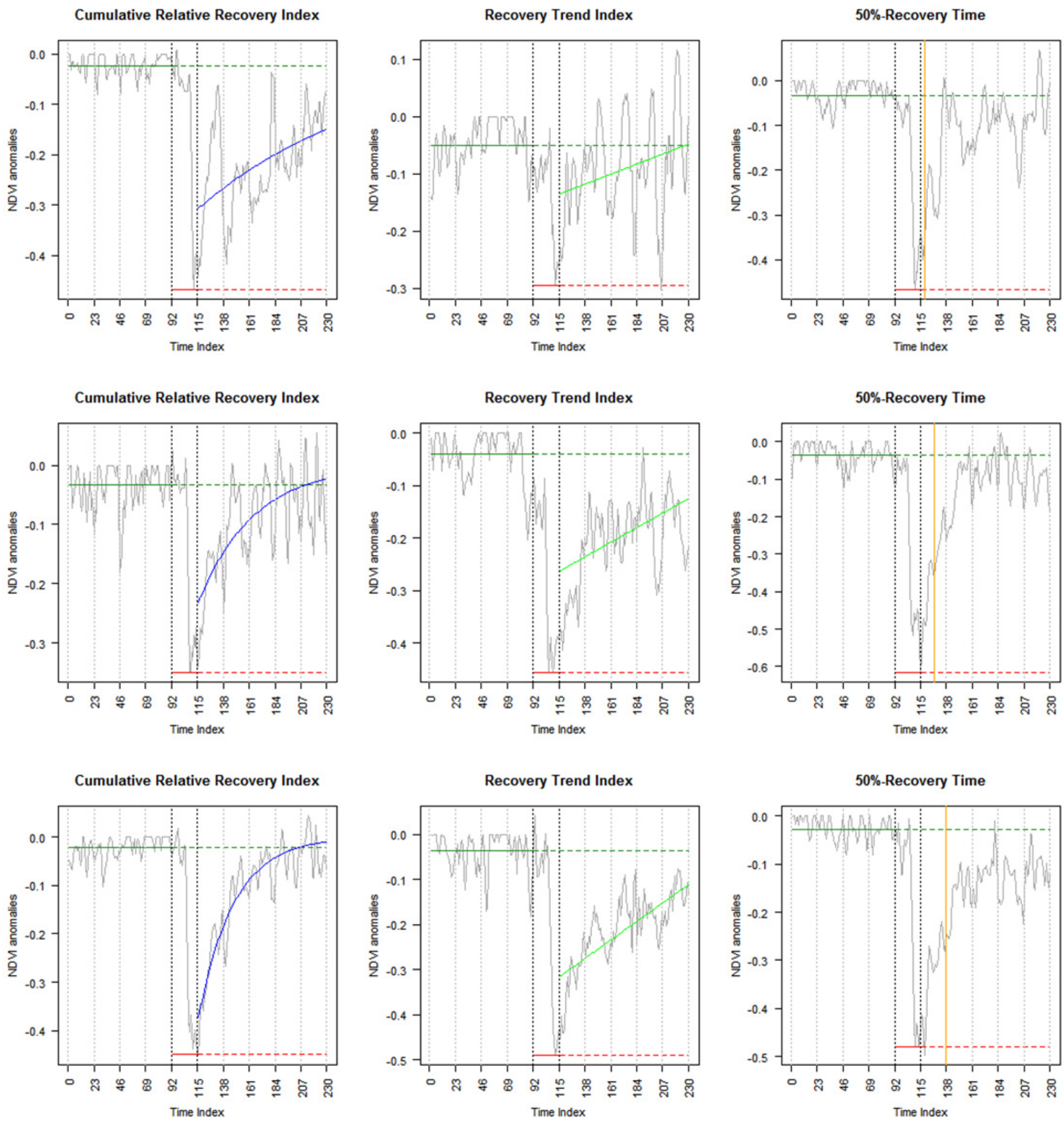


Figure 3.11 Temporal profiles of the NDVI anomalies for burnt pixels (2005) corresponding to the 25% (top row), 50% (middle row), and 75% (bottom row) quantiles of the distributions of each of the indicators of post-fire vegetation recovery used in this study: Cumulative Relative Recovery Index (left column), Recovery Trend Index (middle column), and 50% Recovery Time (right column).

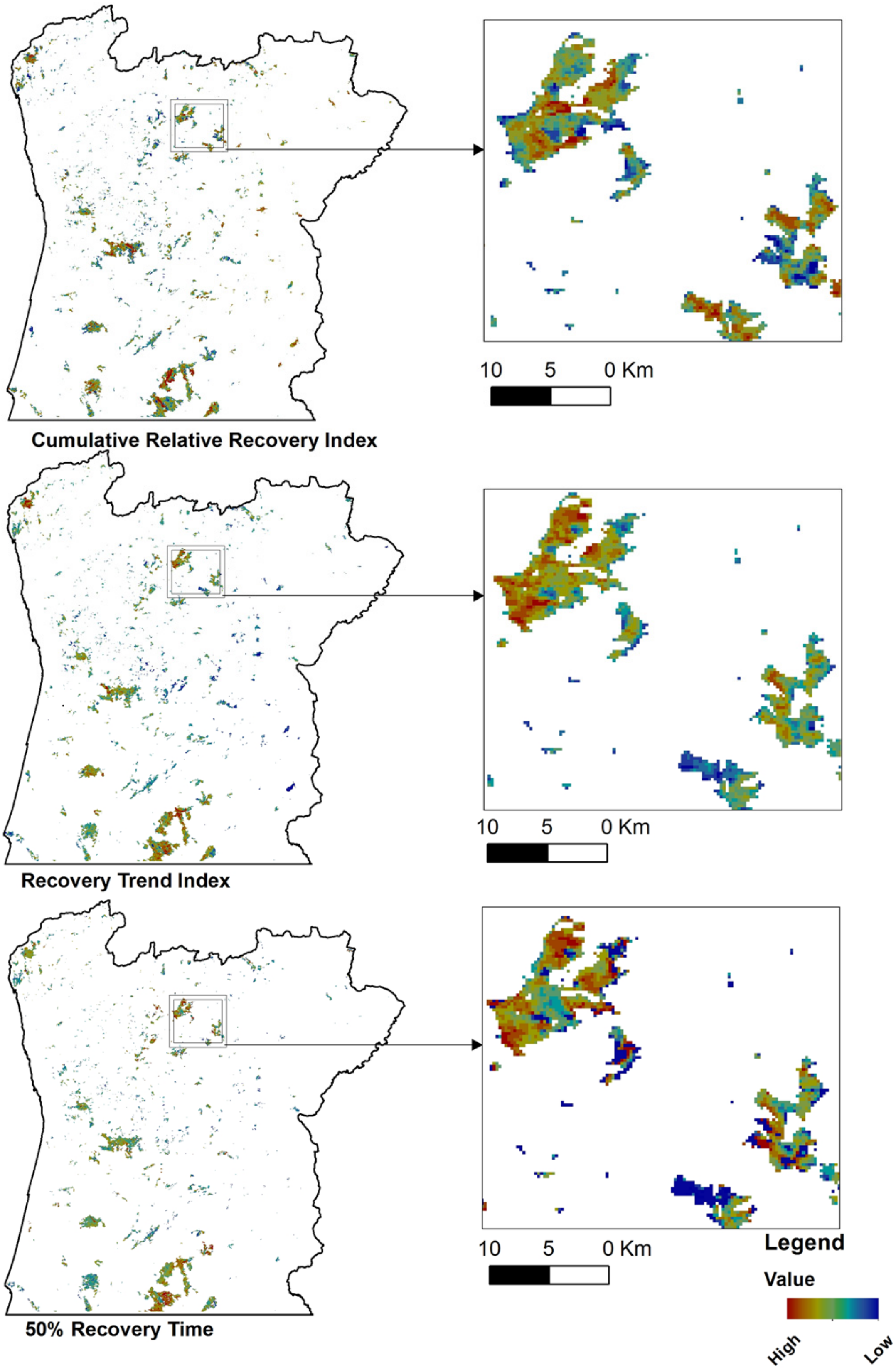


Figure 3.12 Spatial patterns of the three post-fire regeneration indicators assessed in the north of Portugal, for areas burnt in year 2005: Cumulative Relative Recovery Index (top), Recovery Trend Index (middle), and 50% Recovery Time (bottom).

Table 3.9 Cross-tabulation of the three response variables and of the break magnitude index against burnt patch area (in hectares). Median values are presented per area-quantile.

Quantiles	Q25%	Q50%	Q75%
Area of the fire event	(< 413ha) N = 5120	(413 - 3294ha) N = 9375	(> 3294ha) N = 6155
Break Magnitude Index	0.68	0.59	0.51
Cumulative Relative Recovery Index	0.32	0.38	0.41
Recovery Trend Index	0.0010	0.0014	0.0018
50% Recovery Time (days)	55.1	127.9	249.4

3.3.2.2. Model performance and determinants of post fire recovery

Information on model performance (see Methods, section 2.3.2) is provided in Table 3.10 for the three post-fire regeneration indicators. The values for the several performance indicators reveal a good performance of the models for CRRI and for RTI, but a clearly worse performance for the 50%RT model.

Table 3.10 Model performance for the test set, using R^2, Pearson correlation, root-mean-square error (RMSE), and normalized root-mean-square error (NRMSE).

Model (response variable)	R^2	Pearson correlation	RMSE	NRMSE
CRRI	0.85	0.93	4.55E-02	4.81
RTI	0.75	0.87	3.54E-04	4.79
50%RT	0.40	0.63	1.95E+02	12.48

When assessing the relative contribution of each explanatory variable (and group of variables) for the models calibrated for each post-fire regeneration indicator, we found that variables included in the groups expressing fire traits, landscape composition, and pre-fire ecosystem functional attributes were the most important to explain the regional patterns of all three regeneration indicators (Table 3.11). Conversely, variables expressing physical attributes and fire history were of far less importance.

Table 3.11 Ranking of the relative contribution of explanatory variables (and groups of variables) for models calibrated for each response variable (i.e. post-fire regeneration indicator). The top 18 variables are shown so that all groups would be represented by at least one variable.

Rank	Cumulative Relative Recovery Index	Recovery Trend Index	50% Recovery Time
1	Breakmagnitudeindex	Breakmagnitudeindex	Clc_5000m_02
2	Dist_edge_m	Core_brt05	Clc_750m_04
3	Fstats_brn05_sum_750m	Cai_brt05	Clc4
4	Min_MD_2001_2004	CONTIG_brt05	PARA_brt05
5	Fstats_brn05_sum_1500m	Para_brt05	Contig_brt05
6	Ndvitrends20012004slope	Clc_750m_04	CAI_brt05
7	Percentincreasein2004	Clc_5000m_02	Clc_1500m_04
8	Fstats_brn05_sum_5000m	Clc_1500m_04	Dmin_springness_fstats_mn_750m
9	Clc_750m_06	Clc4	Clc2
10	Mean_MD_2001_2004	AREA_brt05	Dmax_winterness_MD_2001_2004
11	Clc4	Clc_5000m_04	Clc_5000m_04
12	Ndvimedian20012004	Dmax_springness_fstats_MN_1500m	Dmax_springness_fstats_MN_750m
13	Clc_750m_04	Dmin_springness_fstats_mn_750m	Dmax_springness_fstats_mn_1500m
14	Elev_m	Clc2	Clc_5000m_05
15	Median_MD_2001_2004	Fstats_brn05_sum_5000m	Breakmagnitudeindex
16	Clc6	Dmin_springness_fstats_mn_1500m	Dmin_springness_fstats_mn_1500m
17	CONTIG_brt05	Dmax_springness_fstats_MN_750m	Dmax_springness_fstats_MN_5000m
18	Mn_burnt_area_90_04	Dmax_winterness_md_2001_2004	Clc_750m_02

Groups of explanatory variables:

Fire traits
Pre-fire conditions/ ecosystem functional attributes
Landscape composition
Physical attributes
Fire history

Fire traits (and particularly the magnitude of the NDVI break induced by the fire event) were the most important factors underlying variations in CRRI and in RTI, whereas landscape composition around each focal burnt pixel was the most important factor underlying the regional variation of the 50%RT indicator (Table 3.11). Pre-fire ecosystem functional attributes and fire traits were particularly important in the case of the CRRI. For RTI, the Fire traits and the Landscape groups of variables were the most explanatory. In the inverse order of importance, these two groups were also the most influential in models for the 50%RT indicator. Overall, there seems to be a shift from functional variables to structural (landscape) variables as we move from the CRRI (expressing long-term recovery) to the 50%RT indicator (short-term recovery) (Table 3.11).

3.3.2.3. Responses of post-fire recovery metrics to key predictors

Figure 3.13 illustrates the response curves of six of the most important variables in models calibrated for the three post-fire regeneration indicators (see also Table 3.11 and Appendix 3).

CRRI (Figure 3.13, top row) was positively influenced by the size of the fire event (‘fstats_brn05_sum_750m’ variable), but negatively influenced by the magnitude of the NDVI break induced by fire (‘breakMagnitudeIndex’), i.e. by fire damage/severity.

RTI (Figure 3.13, middle row) was positively influenced by burnt area landscape metrics. This indicator increased with increasing values of the Core Area Index (CAI), of Core Area (CORE) and of the Contiguity Index (CONTIG) (see Appendix 3, Figure b), suggesting that bigger and spatially more complex burnt patches will have a higher recovery capacity. As expected, this indicator was negatively correlated with the magnitude of the NDVI break, i.e. higher fire damage/intensity led to lower the recovery values.

The 50%RT indicator (Figure 3.14, bottom row) showed a negative correlation with the percentage cover of agricultural areas in the 5000m buffer area around the burnt patch (‘clc_5000m_02’). This suggests that the presence of agricultural areas in a wide area (5000m) around the affected patch decreases the time needed to reach the 50% recovery. Conversely, there was a positive correlation with the percentage cover of coniferous forests in the 750m buffer area of the burnt patch (‘CLC_750m_04’), i.e. the more coniferous forest is found in the surrounding areas, the more time the burnt patch takes to recover. This indicator exhibited more complex responses with the other variables (see Appendix 3, Figure c); also, its models had the poorer performance overall and it exhibited the lowest correlations with the response variables.

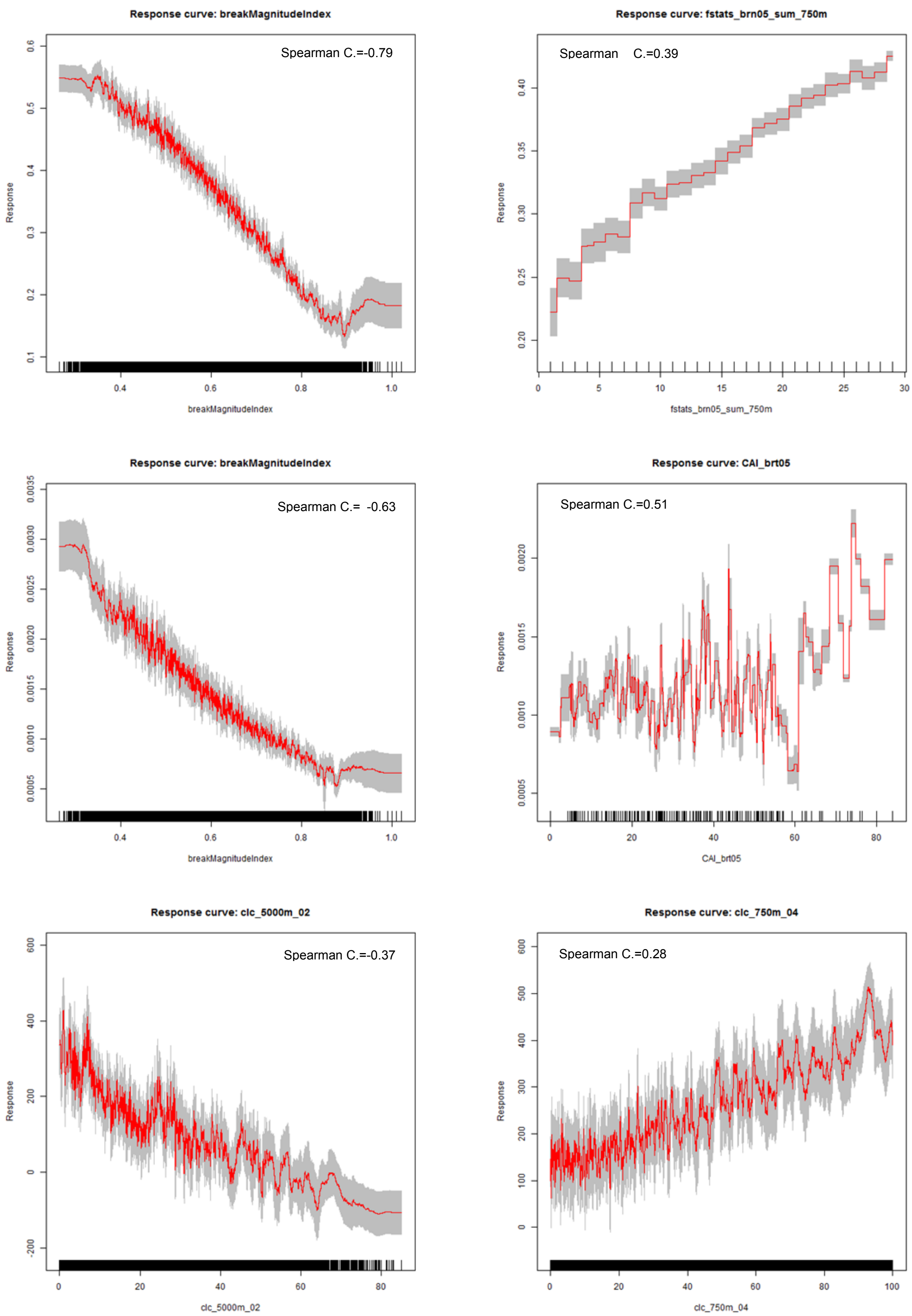


Figure 3.13 Response curves for six of the highest ranked explanatory variables in models for the CRRI (top), for the RTI (middle), and for the 50%RT (bottom). Values for the Spearman correlation rank are also provided.

3.4. Local patterns and drivers of post-fire resilience

3.4.1. Rationale and specific objectives

As described in the Introduction (see section 1.4), local patterns of post-fire vegetation resilience can be influenced by a wide array of factors. These factors can be organized into four general groups: (1) fire history, (2) environmental conditions, (3) pre-fire community structure (incl. vegetation and seed bank), and (4) landscape context.

Fire history (namely frequency and intensity of fire events) is well known as a major determinant of post-fire vegetation resilience (Krebs *et al.*, 2010). However, previous studies of the vegetation of Northern Portuguese mountains have provided evidence that geology and soil factors have a strong influence on early successional vegetation structure and dynamics, namely regarding heath and scrub vegetation (Honrado, 2003). Based on such evidence, here we tested the general hypothesis that, under common climatic and topographic conditions and within one same landscape context, post-fire vegetation resilience is more influenced by lithology/bedrock type (and related soil properties) than by fire history (fire frequency and time since last fire).

Local vegetation resilience can be measured during in-field surveys focused on state variables related to several features of vegetation and plant community structure: (1) vegetation structure (e.g. height and cover of vertical strata), (2) total species richness, (3) species composition, and (4) relative abundance of several functional groups of plants. As described in the Methods section (see 2.2.5), we collected data on vegetation structure and plant community structure from 40 patches differing in fire history and bedrock type. We present below the main results from the analysis of those data under the context of our research hypothesis.

3.4.2. Description and interpretation of results

3.4.2.1. General patterns across strata

Figure 3.14 represents the mean number of plant species per plot for each of the eight strata defined on the basis of bedrock type and fire history. The highest mean value of species richness was observed in plots developed on granitic soils, submitted to multiple fires and with short time distance to the last event. Interestingly, the stratum characterised by schistose lithology and one single, distant fire event was the one with the lowest mean species richness. Overall, the results in Figure 3.14 suggest a tendency for plots from granitic areas (and with occurrence of multiple fire events) to host more species than those from schistose areas (and with a single fire event).

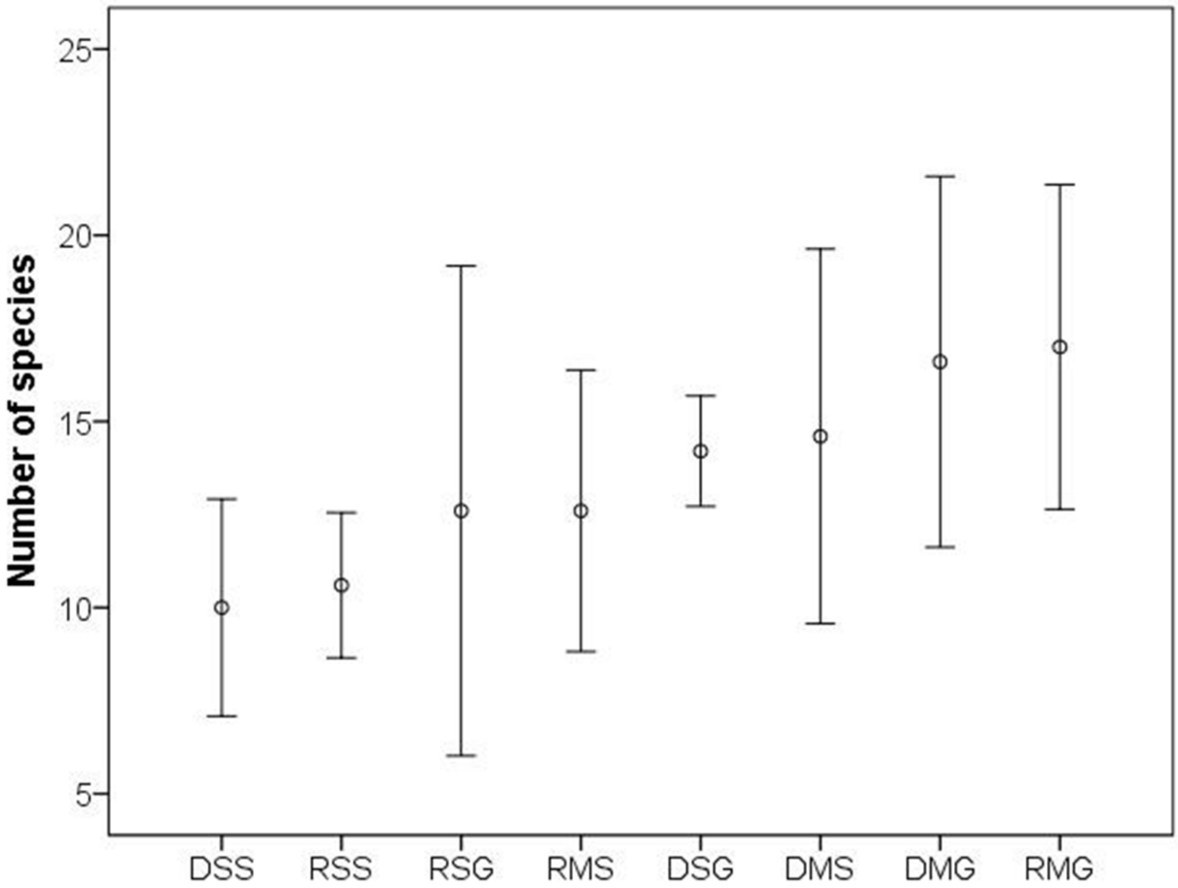


Figure 3.14 Mean (±SD) number of plant species (species richness) per plot across the eight environmental strata. DMG = distant-multiple-granite, DMS = distant-multiple-schist, DSG = distant-single-granite, DSS = distant-single-schist, RMG = recent-multiple-granite, RMS = recent-multiple-schist, RSG = recent-single-granite, RSS = recent-single-schist.

Lithology also had the strongest influence on vegetation structure (Figure 3.15), with plots from granitic areas exhibiting a considerable development of tall shrubs (E1 stratum) in terms of both height (Figure 3.15, top left) and percentage cover (Figure 3.15, top right). Conversely, in plots from schistose areas there was a well developed stratum dominated by low shrubs (E2), with sparse development of tall shrubs. This difference in the development of the dominant shrub strata can be visualized in the photos of Figure 3.15 (bottom left and bottom right). The herbaceous stratum (E3) was also clearly more developed in plots on granite, particularly concerning its percentage cover (Figure 3.15, top left).

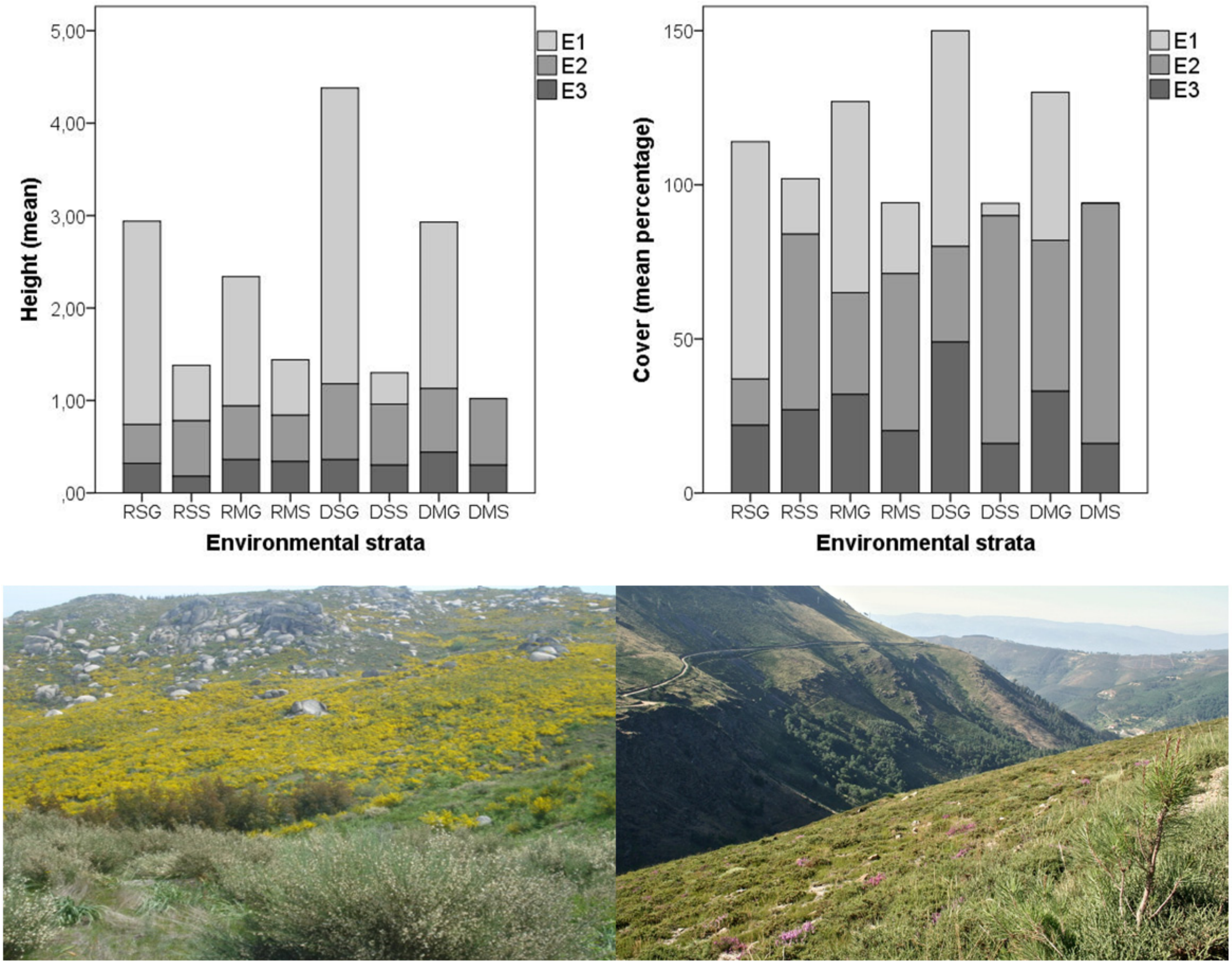


Figure 3.15 Vegetation structure across the eight strata: (top left) height of each vegetation stratum (E1-E3), (top right) cover of each vegetation stratum (E1-E3), (bottom left) example of strong post-fire development of large shrubs (*Cytisus*) on granitic soil, (bottom right) example of low heathland developed on schistose soil. E1 = tall shrubs, E2 = low shrubs, E3 = herbaceous.

3.4.2.2. Specific patterns for woody species across strata

Table 3.12 summarizes the results of the ANOVA tests performed to identify significant differences in the prevalence of functional groups of woody species in strata formed by the three explanatory variables (TSLF, Recurrence, and Lithology). The relations between these variables and the several response variables are depicted in Figure 3.16 to Figure 3.18. Again, there was a prevailing effect of lithology on most of the tested response variables.

Figure 3.16 compares plant species richness between the two time distance classes (i.e. recent fire vs. distant fire), for total species richness and for the several functional classifications. No significant effects of time since last fire events were found for any of the tested response variables, except in the case of seeders (F=5,067; p-value 0,030) and of tall scrub species (F=4,644; p-value=0,038) (Figure 3.16; Table 3.12).

Table 3.12 Results of ANOVA tests for species richness (total and per woody functional group) across the two fire distance strata (distant vs. recent), the two frequency strata (single vs. multiple) and the two Lithology strata (granite vs. schist). Significant differences (p<0.05) are highlighted in bold characters.

	Species richness	F	*p* value	F	*p* value	F	*p* value
		TSLF (distant / recent)		Recurrence (single / multiple)		Lithology (granite / schist)	
	total	0,203	0,655	**6,255**	**0,017**	**5,427**	**0,025**
Response to disturbance	resprouters	0,014	0,908	0,014	0,908	0,122	0,729
	seeders	**5,067**	**0,030**	**5,067**	**0,030**	0,000	1,000
Life forms	trees	0,040	0,843	0,040	0,843	**8,129**	**0,007**
	low shrubs	0,007	0,936	0,325	0,572	**20,520**	**0,000**
	tall shrubs	3,624	0,065	0,951	0,336	**12,897**	**0,001**
Leaf strategy	deciduous	0,206	0,653	0,577	0,452	**13,624**	**0,001**
	evergreen	0,989	0,326	0,000	1,000	**7,156**	**0,011**
	non-leafy	1,159	0,288	**5,104**	**0,030**	0,507	0,481
Synecology	forests and edges	0,628	0,433	0,013	0,911	**8,086**	**0,007**
	low scrub	0,006	0,939	0,728	0,399	**17,433**	**0,000**
	tall scrub	**4,644**	**0,038**	0,875	0,356	**18,291**	**0,000**
Seed dispersal	anemochoric	0,087	0,769	0,801	0,376	**14,597**	**0,000**
	barochoric	3,028	0,090	**5,280**	**0,027**	0,057	0,812
	zoochoric	0,497	0,485	0,497	0,485	**11,217**	**0,002**

When assessing plant species richness between the two fire frequency classes (i.e. single fire vs. multiple fires), for total species richness and for the several woody functional classifications, again few significant effects of fire frequency were found for the tested response variables (Figure 3.17; Table 3.12), in this case for species richness of seeders (F=5,067; p-value=0,030), of non-leafy plants (F=5,104; p-value=0,030) and of barochoric plants (F=5,280; p-value=0,027).

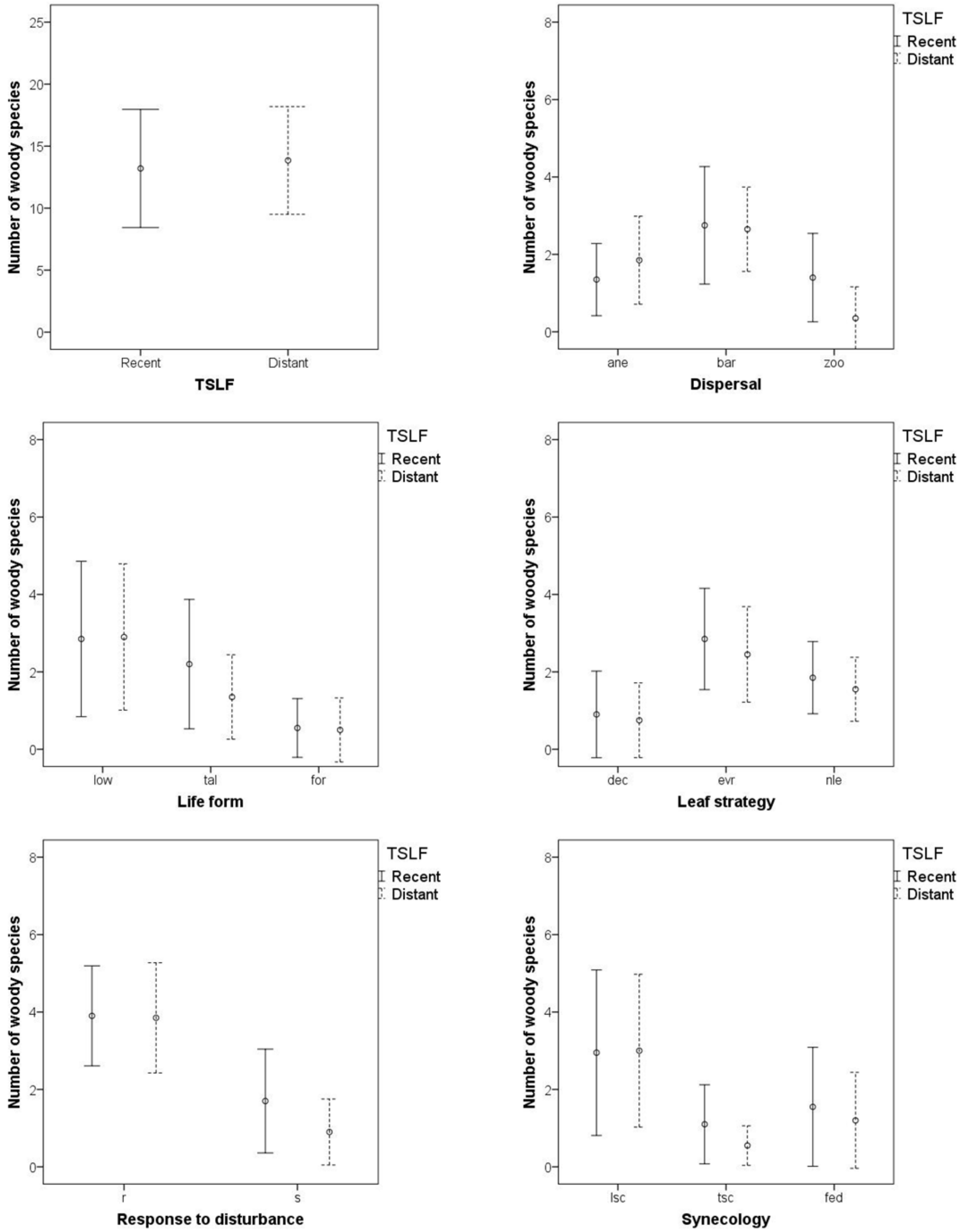


Figure 3.16 Mean (±SD) number of plant species (total and per woody functional classification) across the two fire distance strata (distant vs. recent): (top left) total species richness, (top right) per dispersal type, (middle left) per life form group, (middle right) per leaf strategy type, (bottom left) per type of response to disturbance, and (bottom right) per synecological group.

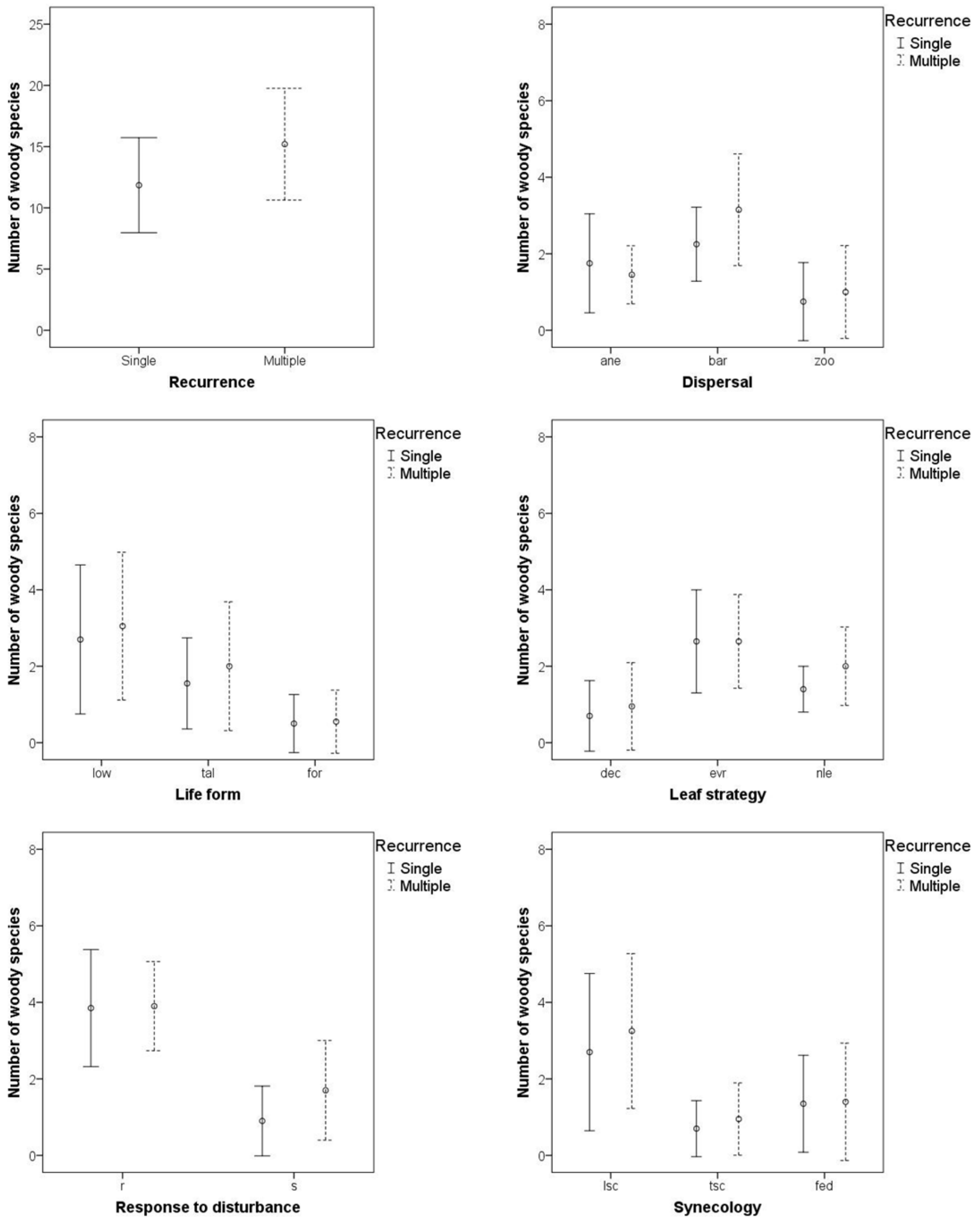


Figure 3.17 Mean (±SD) number of plant species (total and per woody functional classification) across the two fire frequency strata (single vs. multiple): (top left) total species richness, (top right) per dispersal type, (middle left) per life form group, (middle right) per leaf strategy type, (bottom left) per type of response to disturbance, and (bottom right) per synecological group.

Conversely to stratifications based on fire history, when plant species richness was compared between the two lithology strata (i.e. granite vs. schist), for total species richness and for the several woody functional classifications, significant effects were found for most response variables (Figure 3.18). Thus vegetation plots on granite usually host higher numbers of species, of animal-dispersed woody species, of trees and tall shrubs, of woody deciduous species, and of forest, edge and tall scrub species. However, no significant effect of lithology on disturbance response strategies was found (Figure 1.1; Table 3.12).

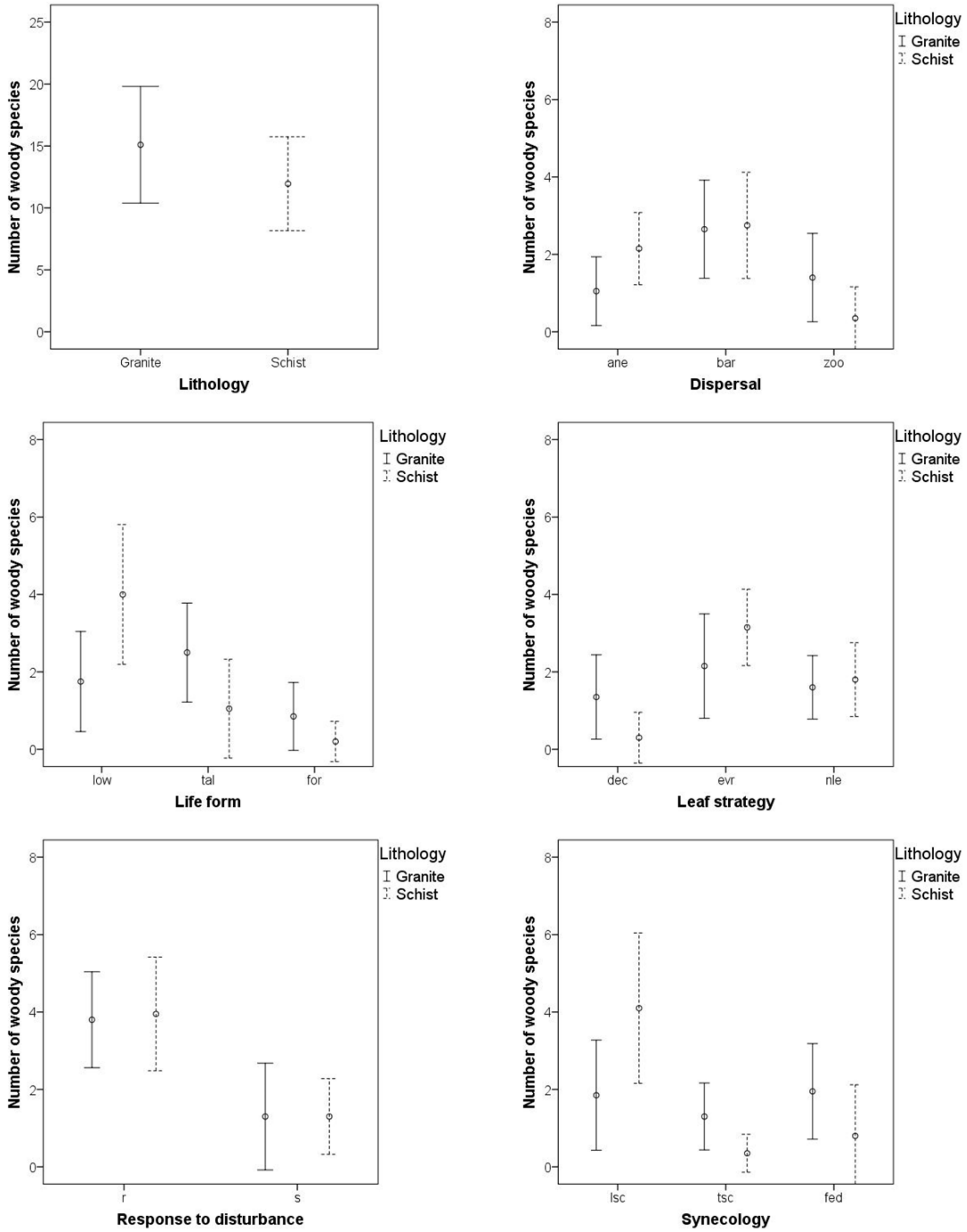


Figure 3.18 Mean number of woody plant species (total and per functional group) across the two Lithology strata (granite vs. schist): (top left) total species richness, (top right) per dispersal type, (middle feft) per life form group, (middle right) per leaf strategy type, (bottom left) per type of response to disturbance, and (bottom right) per synecological group.

3.4.2.3. Effects of fire history and Lithology on plant species composition

Figure 3.19 summarizes the results from the analysis of the general patterns of species composition across the 40 vegetation plots, allowing an inspection of the relation between floristic composition, vegetation structure, fire history, and lithology. The following two main patterns can be inferred:

- the main direction of floristic variation (axis 1 of the DCA plot) is related to differences in the development of the two shrub strata (E1 and E2), which mainly express lithological differences (L); along this first axis, plots on granite are characterised by tall shrubs like *Cytisus* spp. and young trees of *Quercus pyrenaica*, whereas plots on schist are discriminated by low shrubs like *Ericaceae* spp. and *Pterospartum tridentatum*; the higher aggregation of the plots on schist revels a more pronounced floristic homogeneity;
- conversely, variables related to fire history (TSLF and R) have a poor relation with variations of species composition, further confirming the results described in the previous sections for patterns of species richness (total and for species groups).

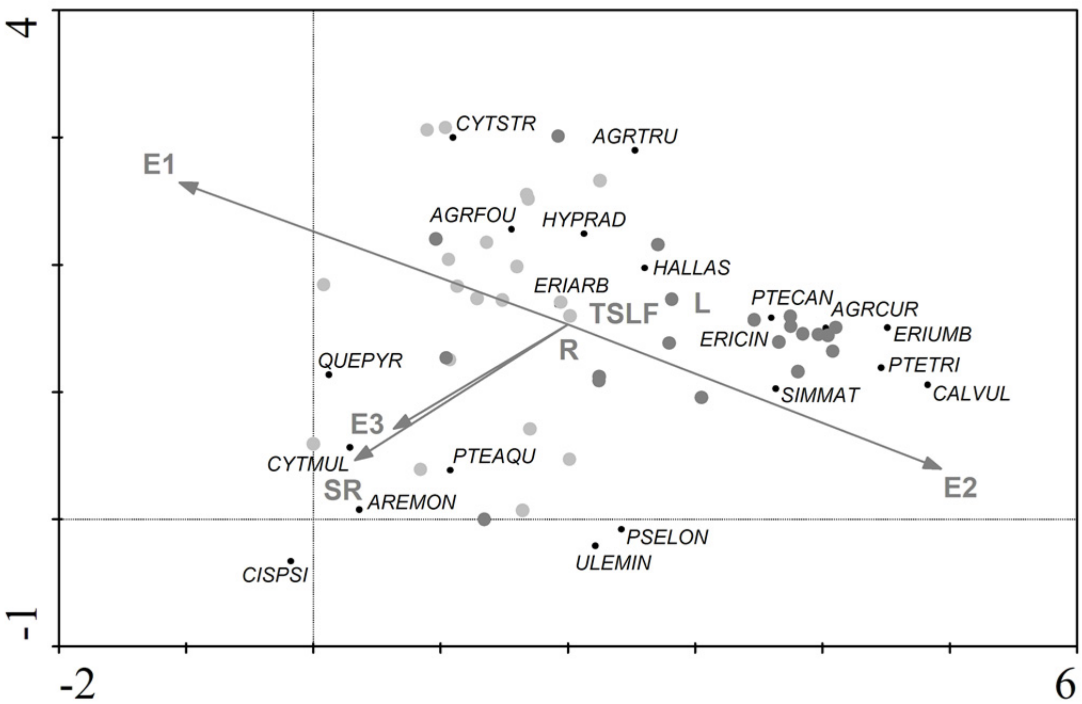


Figure 3.19 DCA ordination plot of species composition for the 40 vegetation plots. Dark grey dots represent plots on schist whereas light grey dots depict plots on granite. Small black dots represent important species. Total species richness (SR), Lithology (L), time since last fire (TSRL), fire frequency (recurrence, R) and vegetation strata (E1-E3) were overlaid passively onto the ordination space.

Analysis of similarities (ANOSIM) aimed to test for differences in community structure as a function of TSLF, Recurrence and Lithology, as well as of their interactions, revealed that:

- there is an interaction between Recurrence, TSLF and Lithology (R=0,35; p-value=0,001);
- there is also an interaction between Lithology and Recurrence (R=0,347; p-value=0,001), and between Lithology and TSLF (R=0,362; p-value=0,001);
- there is no interaction between Recurrence and TSLF (R=-0,012; p-value=0,551).

Given the differences in community composition between plots from granite and plots from schist, and the non-availability of a three-way ANOSIM in the PRIMER software, the data were analysed through a two-way ANOSIM with Recurrence and TSLF for each Lithology type, revealing an interaction between Recurrence and TSLF for plots on granite (R=0,191; p-value=0,016). However, no such interaction was found for plots on schist (R=0,026; p-value=0,327). Overall, differences in species composition were mainly due to Lithology (R=0,457, p-value=0,001). The effect of fire history is significant among granite strata, but only noticeable when comparing the most contrasting combinations of fire distance and frequency.

4. Integrative discussion and conclusions

The results presented in Chapter 3 provide important insights on the patterns and key drivers of wildfire patterns and post-fire resilience at several scales in Portugal, an environmentally heterogeneous country that has been heavily affected by wildfires in recent decades. In this Chapter an integrative discussion of the main results is provided, organized according to the following structure: (i) new insights on the patterns and drivers of wildfire occurrence (mainly based on results in sections 3.1 an 3.2), (ii) new insights on the patterns and drivers of post-fire resilience (results in sections 3.3 and 3.4), (iii) implications of results and insights for planning and management (all results), and finally (iv) synthesis of the main conclusions and perspectives for continued research.

4.1. Patterns and drivers of wildfire occurrence across scales

4.1.1. Spatial patterns of wildfire occurrence in Portugal

A key objective of this thesis was to analyse the patterns and drivers of wildfire occurrence in Portugal, the European country with the highest incidence of wildfires (Pereira *et al.*, 2005). The analysis of wildfire patterns is intrinsically scale-dependent, both in terms of space and time, and it is also highly influenced by the environmental and social-ecological heterogeneity of the regions of interest (Moreira *et al.*, 2001; Catry *et al.*, 2009; Carmo *et al.*, 2011). Therefore, in this thesis wildfire patterns in Portugal were analysed for three distinct spatial contexts/extents: (1) the whole continental area of the country, representing a country level of analysis; (2) the seven agrarian regions of the country, approaching a region level analysis; and (3) the elevation gradient of the Alto Minho, in the northwest of the country, at a sub-region level.

4.1.1.1. Assessing wildfire patterns in heterogeneous countries

The analysis of wildfire patterns in the whole mainland Portugal confirmed a highly heterogeneous distribution of fire events across the country. In fact, in the period between years 1990 and 2010, most fires occurred in the northern half of the country where rainy Mediterranean climates prevail and high biomass accumulation coincides with a dry summer season (Catry *et al.*, 2010) and the corresponding phenological fire-proneness of vegetation (Keeley *et al.*, 2011). This is consistent with reports from other Mediterranean countries in Europe and elsewhere, e.g. Spain, Greece, and Morocco (Pausas *et al.*, 2008). In the same period, Portugal was the country with most fire events per area across Europe (Pereira *et al.*, 2005), which further highlights the importance of understanding the patterns and drivers of wildfire occurrence in this country.

In our study, when using the whole country as test area to model wildfire patterns, the best results were obtained when using the whole set of variables (see Table 3.1), generating a model with low parsimony while at the same time highlighting the complexity of the problem and the diversity of factors involved in fire ignition and behaviour (Gill *et al.*, 2013). Also for the whole country, the landscape group of variables had the best individual performance (i.e. the closest to using the whole set of variables; see Table 3.1). This was probably due to the fact that land use and landscape patterns are considered a synthesis of multiple environmental, social and economic effects (Mücher *et al.*, 2010), and thereby capable of capturing the effects of a wider range of fire factors (Carmo *et al.*, 2011).

The several agrarian regions of mainland Portugal have recorded rather distinct fire regimes in the focal period (see Results, section 3.1.2). The regions with the highest number of fire events corresponded to those located in the Centre and Northwest parts of the country (see Figure 2.18 and Table 3.1). In general, these regions are characterised by moderate to high topographic complexity, warm summers, varying population densities, and by forest, scrub and rain-fed crop fields dominating the land cover. Here, models using all variables attained good performances, even better than for the whole country in the case of the EDM region (extreme northwest of the country), highlighting the complexity of fire regimes in this heterogeneous region (see Figures 3.1 and 3.2, and regional study in section 3.2). Conversely, the regions affected by fewer fires were located in the South and are characterised by a low topographic complexity, drier and more Mediterranean climates, low levels of population density, and dominance of extensive agriculture and agro-forestry systems. Similar patterns have been reported for the whole Iberian Peninsula (Pereira *et al.*, 2010).

Through the use of blocks of variables it was possible to analyse their relative importance across the country (see Figure 3.3). In the northern part of the country the use of the whole dataset produced the best results, but in the southern part that was not the case. In the Ribatejo and Oeste region the best results were obtained by using the socio-economic block of variables. This is a highly urbanized region, with strong contrasts between the large urban areas and the surrounding rural territories, so these results confirm a strong influence of socio-economic factors in explaining fire history in such contrasting regions (Chuvieco *et al.*, 2013). The most southern regions of Alentejo (with very few fire events) and Algarve, the topographic block of variables revealed to be very influential, probably reflecting not only the effect of topography itself on fire patterns (Carmo *et al.*, 2012), but also its influence on land cover, climate, and socio-economy, particularly in regions with relatively low demographic densities (Wood *et al.*, 2011). Overall, our results for the relative importance of blocks of variables (see Figures 3.3 and 3.5) highlight not only that fire history is very different throughout the country, but also that it can be best explained by different factors in different regions, supporting the importance of regional analyses when exploring wildfire causes (Costa *et al.*, 2010).

To further explore the complexity of fire regimes in the several regions of Portugal, we assessed the relative performance of each single block of variables in comparison to using all the variables, in each region (see Figure 3.4). As described before, in the four northern regions model performance was significantly worse when using only one block of variables, nonetheless the landscape block had consistently the minimum amount of performance loss. The socio-economic variables performed quit poorly in all four regions, which is surprising considering the importance of human activities as fire factors (Aldersley *et al.*, 2011) but can probably be attributed to a fairly high internal homogeneity of socio-economic features in these regions, particularly in their rural parishes, where most fires occur (Pereira *et al.*, 2011). Conversely, the three southern regions all attained significantly better results when using only one block of variables than when using the whole dataset. In the Algarve, using only the topographic block of variables represented a gain of over 25% in model performance (see Figure 3.4).

Overall, our results provide evidence that landscape variables are the most important to explain fire history in the Northern part of the country, whereas topographic and socio-economic variables are more important in the Southern areas (see Figure 3.5). The low importance of climate variables to explain wildfire patterns at the regional scale (for the whole country and for individual regions) is by itself evidence of the strong human mediation of current fire patterns in the country, when compared to those that could be expected according to the biophysical conditions of each region (Aldersley *et al.*, 2011). This does not, however, contradict the well-known importance of weather conditions in the features of fire events (Macias Fauria *et al.*, 2011) or the influence of climate on vegetation, land use and fuel biomass patterns (Holz *et al.*, 2012), which may have been captured by the landscape variables in our analyses.

Methods based on Support Vector Machines (SVMs) have been particularly successful in applications where the dataset includes a large set of variables (Tax and Duin, 2004). SVMs use a functional relationship known as a kernel to map data onto a new hyperspace in which complicated patterns can be more simply represented (Müller *et al.*, 2001). Because SVMs are not based on characteristics of statistical distributions, there is no theoretical requirement for observed data to be independent, thereby overcoming the problem of auto-correlated observations, although model performance may be affected by how well data represent the range of environmental conditions (Austin, 2007). Furthermore, SVMs are more stable, require less model tuning, and have model performance will be affected by how well the observed data represent the range of environmental variables fewer parameters than other computational optimization methods such as neural networks (Lusk *et al.*, 2002). In our SVM-based assessment of national and regional fire patterns, the proportion of the area that burnt in each of the seven regions during the focal time frame was rather different (see Table 3.1), which may have been one of the causes of the asymmetric performance exhibited by the algorithm. On average, the civil parishes of the four northern regions (EDM, TM, BL, BI) had more than 16% of their territory burnt in the time frame considered, whereas in the southern regions this value was always below 6% (see Table 3.1). Variations of mean fire recurrence and proportion of parishes with more than 10% burnt area may have been other causes for the observed differences of algorithm performance (Lozano *et al.*, 2012). The inferior number of observations (i.e. civil parishes) and the higher proportion of non-zero observations (i.e. civil parishes without any fire record) in the southern part of the country are other factors to consider, since with a small number of observations and a large number of descriptive variables most modelling techniques tend to suffer from the well-known "curse of dimensionality" (Bellman, 1961), which may also explain the better results obtained when using only topography variables in models for the southern regions. Including better climatic, vegetation and land use/cover data (especially in terms of spatiotemporal resolution), variables related to socio-economic trends or changes (e.g., population variation and ageing) as well as other factors characterizing spatial propensity to fire ignition (Moreira *et al.*, 2010) and accessibilities to natural spaces (Romero-Calcerrada *et al.*, 2010) could also improve modelling routines.

4.1.1.2. Assessing wildfire patterns in heterogeneous regions

The analysis of spatiotemporal patterns of wildfires at the sub-regional level in the Alto Minho, northwest Portugal (see section 3.2), revealed that ILP-based machine-learning techniques can also be useful to analyse fire patterns in smaller geographic contexts, provided that that there are enough wildfire data and spatial heterogeneity of environmental conditions to support the development of a robust classification rule set. Fire occurrence is a complex phenomenon and so we could hardly expect to fully explain and predict fire patterns in heterogeneous regions based on small sets of information on the potential drivers (Chuvieco et al 2013; see also our study of the national fire patterns, section 4.1.1.1). However, our results do provide further support (in this case for fire pattern analysis) to the usefulness of machine-learning techniques in addressing complex ecological or environmental problems such as the spatial distribution of endangered species (Shan *et al.*, 2005), mapping land-cover modifications (Rogan *et al.*, 2008), post-wildfire land-cover mapping (Brunby *et al.*, 2002), and classifying and mapping wildfire severity (Brewer *et al.*, 2005).

In our study, a rule set consisting of 15 rules was able to predict more than 80% of the burnt areas (i.e. high Recall) in the 1991-2000 time frame (training dataset), though with a rather low Precision (20%; see Table 3.3). This demonstrates the ability of ILP to capture a large proportion of patches that burnt throughout a decade, using a relatively low number of rules. Even if a large number of unburned areas are also captured by those rules, the rule set describes the main features of burnt areas and therefore it may play an important role as a predictive tool, which would be an important asset for fire risk assessment, mapping and management (Chuvieco *et al.*, 2010; see below) at patch-level resolution. Interestingly, when applied to an independent test dataset (burnt areas in the 2001-2010 time frame) and using a substantially different land cover dataset, this rule set was able to maintain a relatively high Recall, predicting almost 70% of the actually burnt areas, and even with a higher Precision (28%; see Table 3.4). This rule set therefore does seem capable of predicting some patterns of wildfires in the region at a decadal resolution. This may also stress some temporal stability of forest fire drivers in the sense that we did not observe strong changes in prediction performance of the rule set from one decade to the other. Additionally, this fact itself highlights the fairly good generalization ability of the ILP-ML technique used.

The rule set identified land cover and bedrock type as the main factors explaining the spatiotemporal patterns of wildfires in the Alto Minho (see section 3.2.2.3). The presence or proximity to several types of forest areas were particularly frequent across the rule set (11 of the 15 rules), particularly if the analysed patch was neighboured by pine or eucalypt patches. In fact, these tree species, extensively planted in the region and across the country, are known to favour the propagation of fire due to their life history traits (Pausas and Schwilk, 2012), often in conjunction with neglected management (Rego *et al.*, 2013). The presence of (or proximity to) scrubland areas (6 rules) and sparsely vegetated areas (4 rules) was also, as expected, important in the formulation of the rule set. These land cover types are dominant in many fire-prone landscape mosaics, particularly those where the use of fire as a landscape management tool (e.g. for pasture regeneration and scrub clearing in highlands) is still common (Moreira *et al.*, 2011). The importance of bedrock type (8 rules) confirms the relevance of geological features (and their influence in the vegetation cover; Capelo *et al.*, 2007) in fire ecology, from the occurrence of wildfires (Costa *et al.*, 2013) to the patterns of post-fire regeneration (see sections 3.4 and 4.2.2).

An important fact to consider is that, since the description of wildfire regimes is scale-dependent, the outcomes of their analysis may also be very much influenced by the quality of fire data (Thompson and Calkin, 2011). The national wildfire database used in our study presents some important limitations for fire pattern analysis, such as the absence of a specific date for each fire (only the year is reported) or the absence of indication of fire intensity or severity. Moreover, fires with burnt area below five hectares are not included. Nonetheless, those limitations can be most important for local studies, but less for those at regional scales. In fact, this database has been thoroughly used to address national and regional patterns of wildfires in the country (e.g. Catry *et al.*, 2009; Moreira *et al.*, 2009, 2010).

This study was possible due to the recent development of sophisticated geographical databases that led to advances in spatial data analysis and mining, defined to be the branch of data-mining where the spatial neighbors of an object may have an influence on the object (Ceci *et al.*, 2009). The description and interpretation of wildfire regimes will always be influenced by the chosen analytical framework (Krebs *et al.*, 2010). We believe that coupling an ILP system with a logic-based geographic information system we avoided the off-line materialization step of spatial features using external geographic information systems, allowing the search process to dynamically explore spatial relationship predicates in the formulation of clauses. In this way we obtained a novel and promising approach to the study of intricate spatial relations as those between wildfires, land cover, and environmental conditions.

4.1.2. Drivers of wildfire occurrence: the importance of considering heterogeneity

The results presented in this thesis provide support to the view that the analysis of the drivers of wildfire patterns should consider not only the scale-dependence of those patterns (Moreira *et al.*, 2010), but also their context-dependence, particularly when analysing environmentally and social-ecologically heterogeneous countries or regions (Nunes *et al.*, 2005). In this thesis, drivers of wildfire patterns in Portugal were thus analysed for several distinct spatial contexts and resolutions, from the whole continental area of the country (and the seven agrarian regions therein) to the elevation gradient of the Alto Minho sub-region, in the northwest of the country.

The diversity of climatic, topographic, socio-economic and landscape conditions in Portugal (see Methods, section 2.2.1) originates contrasting fire regimes across the country (Catry *et al.*, 2010; Costa *et al.*, 2010). The modelling framework applied in our study of national pattern of wildfires yielded several important clues towards a deeper understanding of the causes underlying this variability. First, it demonstrated that the country is clearly divided in two parts regarding its wildfire regime (see Figure 2.18 and Table 3.1). As discussed above, in the northern half of Portugal fire patterns are better explained when considering the effects of multiple factors (i.e. when using the whole set of variables). Clearly contrasting with this, in the southern half of the country models based on the whole set of variables were always outperformed by models based on a single block of variables. In part, this may be due to the lower number of observations (i.e. civil parishes) and the higher proportion of non-zero observations (i.e. civil parishes with no fire recorded) in the southern part of the country, as discussed above.

Second, our modelling framework also highlighted that the relative importance of the several types of drivers of fire regime is highly variable across regions (see e.g. Figures 3.4 and 3.5, and Table 3.2). For example, landscape variables represented the most important block in most of the northern agrarian regions, where it exhibited lower loss in model performance, whereas topography and socio-economy seem to be the most important effects in the southern part of the country. In the Southern region of the country, and particularly in the Algarve, wildfires are very concentrated in areas with higher elevation or inclination, so the model based on topographic variables holds a good performance (see Figure 3.5 and Table 3.2). Consistently with previous reports (e.g. Moreira *et al.*, 2010; Nunes *et al.*, 2005), these results suggest that the drivers of fire history in Portugal must be analysed separately per region, and would recommend a regionally stratified planning of fire risk management (see below).

The detailed analysis of wildfire patterns and drivers in the Alto Minho region further highlighted the importance of considering (sub-)regional heterogeneity of environmental conditions and social-ecological contexts to adequately interpret the main features of disturbance regimes (Turner, 2010). Through the development of inductive logical rules, various combinations of land cover (particularly presence of forest and scrub) and bedrock type were found to explain distinct sets of burnt patches in the period between years 1991 and 2000 (see Table 3.8). This same combination of factors successfully predicted burnt areas in an independent dataset from the following decade (2001-2010). Even in a small (but rather heterogeneous) region, several factors thus emerged, under multiple combinations, as determinants of wildfire occurrence. Moreover, these factors explain fire patterns with contrasting spatial incidence in the region, since the several rules have quite different spatial coverage in the study area (see e.g. Tables 3.6 and 3.7).

Surprisingly, climatic factors were not selected to formulate any of the 15 rules in the final rule set (see Table 3.8). Climate is usually reported as an important driver of wildfire patterns (Slocum *et al.*, 2010; Fauria *et al.*, 2011) and therefore it is considered in wildfire risk modelling (Bradshaw *et al.*, 1984; Moriondo *et al.*, 2006). However, according to our results, in the Alto Minho the spatial variations of temperature and precipitation are not greatly related with the occurrence of wildfires, even if climatic gradients are quite sharp in the region (see section 2.1.3). Rather, other factors influencing complex ecological patterns at more local scales (Vicente *et al.*, 2011), namely related to land use/cover and geology, emerged as key determinants of wildfire occurrence. This is consistent with the results obtained in our national assessment for the EDM region, where the landscape block of variables was the best performing one (see section 3.1.2). Even considering that the relative importance of factors may be different in other regions with distinct patterns of environmental and socio-economic conditions (see e.g. section 3.1), the rule set obtained in this study highlights the importance of testing the effects of all plausible factors (but particularly those related to, or constraining, patterns of land use) in order to obtain robust, tailored predictions and thereby improve fire risk modelling and management (see below).

4.2. Patterns and drivers of post-fire resilience across scales

The patterns of post-fire ecosystem resilience, as those of any spatially-structured ecological process, are intrinsically scale-dependent, as they are very much related to the spatiotemporal patterns of conditions, resources and disturbances (Parisien *et al.*, 2011). Therefore, in this thesis results from two studies were presented, the first one using remote sensing tools to assess regional patterns of post-fire regeneration based on functional indicators (see section 3.3), and the second one describing the local controls of resilience analysed from in-field vegetation data and focused on vegetation and plant community structure (see section 3.4).

4.2.1. Assessing post-fire resilience at the regional scale from remote sensing data

4.2.1.1. Indicators of post-fire recovery of early successional vegetation

Detecting ecological disturbances and other environmental pressures across large areas can benefit from the application of remote sensing (RS) data, products and techniques (e.g. Nagendra *et al.*, 2012). In fact, RS approaches have been used previously to identify functionally homogeneous regions (Alcaraz *et al.*, 2006) as well as to predict fire incidence through fuel phenology (Bajocco *et al.*, 2010) or distribution of ecosystem functional types in temperate South America (Paruelo *et al.*, 2001).

Remote sensing tools have been used to assess the responses of ecosystems and landscapes to several types of disturbances, from floods and landslides to deforestation and wildfires (Joyce *et al.*, 2009; Sena *et al.*, 2013; Van Linn *et al.*, 2013). In our regional study of fire patterns in the northern part of Portugal, fire events could successfully be noticed in their effects on indicators of ecosystem functional dynamics. In fact, a strong and abrupt decline in the NDVI curves was observed in the pixels burnt in year 2005, our focal year for wildfire analysis (see Figure 3.11).

To address regional patterns of post-fire regeneration, we developed and tested three functional indicators related to ecosystem productivity and phenology: The Cumulative Relative Recovery Index (CRRI), the Recovery Trend Index (RTI), and the 50% Recovery Time indicator (50%RT). Considering their distinct definitions, covering different rates of post-fire recovery, and the fact that they were not highly correlated in the test region (see Table 2.11), these three indicators were expected to allow assessing distinct (and complementary) dimensions of the regeneration process, jointly allowing a more integrative view of functional resilience, which is a key component of ecosystem resilience (Lavorel, 1999; Pausas and Lloret, 2007; Moretti and Legg, 2009).

These three response variables yielded distinct statistical distributions in the study region. In the CRRI the distribution was very similar to Gaussian (i.e. Normal), the RTI also had a distribution fairly close to Normal, but the 50%RT had a more asymmetrical distribution, with a high percentage of the values concentrated in the first 400 days after the beginning of the first post-fire year, and even some negative values recorded (see Figure 3.10). Moreover, these indicators also differed in the fact that, in the case of CRRI (an integral below a smoothed curve) we are modelling to predict an area (more sensitive to small changes and local maximums), in the RTI we derived the trend (linear trend), with the natural error associated from observing a seasonal phenomenon, and in the 50%RT we tried to predict a point (a specific date in which the NDVI recovery will reach 50% of the pre-fire median), which holds the highest degree of uncertainty. Moreover, as the CRRI results of a normalized cumulative sum of the observed values (without modelling), and the RTI and 50%RT indicators were obtained by nonparametric linear models (being the one for 50%RT more complex and with interactive automatic adjustments), a gradual decrease in model performance was expected, and it was actually observed (see Table 3.10).

The ranking of the relative contribution of explanatory variables (and groups of variables) revealed differences between models fitted for the three regeneration indicators (see Table 3.11). Models for CRRI was the only case that included variables from all five groups (in the top ranked 18 variables), although most of the variables were related to the "fire traits" and "ecosystem functional attributes" groups. The variable with the highest predictive importance for explaining CCRI variability was the Break Magnitude Index i.e. the relative magnitude of the NDVI break caused by the fire event. This was also the highest ranking variable in models for RTI (see Table 3.11); for this indicator, the groups of variables with highest importance were "fire traits" and "landscape composition". The latter was the group of variables with highest importance for the 50%RT indicator (see Table 3.11).

These results suggest that the three response variables express different aspects of the recovery process, occurring at different temporal scales (short vs. mid-long term) and responding to variables which themselves exhibit distinct patterns in space (intra-patch vs. landscape context) and time (pre-fire conditions vs. features of the fire event). For the CRRI, the pre-fire conditions and the features of the fire event itself are the dominant constrains to the recovery process; also, this indicator seems to express the mid-long term regeneration of ecosystem functioning (e.g. Leeuwen *et al.*, 2010) and it is closely related with the functional constraints (pre-fire and fire event) of the recovery process. In the case of the RTI, the features of the fire event and the landscape context are the more important factors; this indicator therefore responds to a mixture of functional and structural constraints of the recovery process. Finally, in the case of the 50%RT indicator, which appears to refer more to the short-term stage of the recovery process (Bastos *et al.*, 2011), the landscape context (structural features) was identified as the prevalent factor.

Overall, from the CCRI and the RTI to the 50%RT indicator there is a general shift from the functional constraints characterising the burnt patches (i.e. pre-fire conditions and changes induced by the fire event), which seem to be key drivers of the mid-long term recovery, to the structural features of the surrounding landscapes, which seem to be more related with the short-term responses to fire disturbance. One hypothesis to explain this result is that the short-term response in the burnt patch may be dependent of the landscape availability of seeders / ruderal species that can converge rapidly to the newly open area (Pate *et al.*, 1990), whereas the mid-long term regeneration may be more determined by the survival of late-successional resprouting species inside the burnt patch, which in turn mainly depends on the pre-fire condition of vegetation and on the intensity and severity of the fire event (Malkisnon *et al.*, 2011). The contribution of early successional habitats to overall species richness can be larger than those of late successional habitats due to a higher heterogeneity between burnt areas caused by dispersal limitation (Brotons *et al.*, 2005).

4.2.1.2. Drivers of post-fire resilience at the regional scale

The results obtained in our study of regional patterns of post-fire regeneration give support to the notion that when addressing post-fire recovery we have to be very careful in stating what exactly are we measuring (Díaz-Delgado *et al.*, 2002; Leeuwen *et al.*, 2010; Bastos *et al.*, 2011). In this case our three indicators of post-fire functional regeneration of vegetation were found to respond to different sets of factors, and they seem to express distinct and complementary dimensions of the regeneration process, as discussed in the previous section.

In the CRRI and RTI indicators, the “break magnitude index” was the variable with the highest rank and (by far) with the highest correlation with the response variables (see Table 3.11). This index translates the relative decrease in NDVI produced by the fire event regarding the pre-fire NDVI mean, so it expresses the severity (and thus also the relative intensity) of the fire event and it was expected to reflect negatively on the recovery process (Bastos *et al.*, 2011; see Figure 3.13). In fact, there is a well-known relation between fire severity and post-fire regeneration, with more severe fires causing a higher depletion of the regeneration capacity of burnt areas whereas less severe fires are often followed by rapid recovery in at least some resilience indicators (Diaz-Delgado *et al.*, 2002; Leeuwen and

Casady, 2010).

In CRRI and in RTI, the recovery measured was more intense in areas (i.e. pixels) that were located far from the edge of burnt patches (see Table 3.11, Figure 3.13, and Appendix 3, Figures a and b). This could suggest that core areas would recover better than those located in the edge of the burnt patch, which would seem a counterintuitive result (Leeuwen *et al.*, 2010). Instead, we hypothesized that this result may be expressing an effect related to burnt patch size. We tested this by analysing fire severity and regeneration indicators against fire event size. The NDVI break magnitude had a significant (p-value < 0.001) negative correlation with fire size, meaning that with decreasing break magnitude, fire size increased (see Table 3.9). Conversely (but as expected given the previous result), the values for the CRRI and RTI recovery indicators increased with the size of the burnt area. However, the time required to obtain a 50% NDVI recovery (i.e. the 50%RT indicator) increased as burnt area size increased.

Overall, small fires recorded the largest fire severities (i.e. as measured by the decrease in NDVI), which reflected on lower capacity of mid-long term regeneration, probably due to higher mortality of late-successional resprouters in the burnt patch (Malkisnon *et al.*, 2011). Small fires also recorded the highest capacity for short-term recovery, which is likely the result of higher propagule pressure by seeders / ruderals from the surrounding landscape (Pate *et al.*, 1990). These small fire events may have occurred in complex landscapes with high local (but discontinuous) accumulation of fuel biomass, which favour small but intense fires (Moreira *et al.*, 2001; Pereira *et al.*, 2005).

Conversely, large fires recorded lower values of NDVI break magnitude (i.e. lower fire severity) and consequently the mid-long term regeneration was higher than in small fires. These events may represent large mountain fires, usually spreading over areas where fuel biomass accumulation is locally small but rather continuous across the landscape, creating suitable conditions for large fires with low to moderate intensity (Fernandes *et al.*, 2010). Areas burnt during large fires yielded the lowest values of short-term recovery, probably due to lower propagule pressure from the surrounding landscape over the larger core area of burnt patches (Larios *et al.*, 2013).

The importance of landscape variables, particularly for the RTI and 50%RT indicators, suggests a connection between post-fire regeneration and productivity/benign soil conditions, which are more common in farmland matrices than in forest matrices (Lunt *et al.*, 2012). In the 50%RT models, landscape variables are even preponderant, with the presence of agricultural areas in the wider landscape decreasing the time needed to reach a 50% NDVI recovery and the presence of coniferous forests in the surroundings of the burnt patch increasing the time it takes to recover (see Figure 3.13). The fact that the effects of these structural landscape variables are felt at different distances around the focal burnt pixel (see

Table 3.11 and Figure 3.13) highlights the importance of a multi-scale approach to the effects of landscape structure on fire occurrence and on post-fire recovery (Morgan *et al.*, 2001; Lozano *et al.*, 2010). It also highlights again the importance of considering ecological heterogeneity in the assessment of fire regimes and post-fire processes, as discussed in previous sections.

A surprising result from our regional assessment of post-fire resilience was the apparent low importance of variables from the “physical attributes” and “fire history” groups. Only in models for CRRI these variables entered the list of 20 top ranked variables, and still only among the lowest ranked (see Table 3.11). Physical environmental attributes (e.g. climate, topography) and features of the fire regime (e.g. recurrence, distance to last fire) are vastly used in studies of fire occurrence (Pausas *et al.*, 2008; Ganteaume *et al.*, 2013) and post-fire recovery (Clemente *et al.*, 2006), but they were of seemingly low importance in our models for functional indicators of post-fire regeneration. These results thus suggest that, when compared with structural approaches, using functional indicators to assess post-fire regeneration may capture dimensions of resilience that are influenced by a distinct set of drivers (Díaz-Delgado *et al.*, 2002; Leeuwen *et al.*, 2010).

4.2.2. Assessing the local controls of post-fire vegetation resilience

Local ecosystem resilience after disturbance can be influenced by multiple factors, as described in the Introduction (see section 1.4.4), from the spatial distribution of conditions, resources and disturbances to pre-fire structure of biotic communities (Lavorel, 1999). On nutrient-poor, shallow soils of many mountainous regions across Europe, fire history (often joined by grazing) usually originates vegetation mosaics consisting of scrub, grasslands and patches of woodland at different stages of successional development (Acácio *et al.*, 2009). Our study of the local controls of post-fire resilience focused on these landscape mosaics, and particularly on scrub communities originated by vegetation recovery after fire in the mountains of northern Portugal. The diversity and dynamics of these vegetation types in the region are known to be controlled by climate, geology, topography, and human management (Aguiar, 2001; Honrado, 2003). In the study developed for this thesis we hypothesized that, under comparable climatic and topographic conditions, geology (particularly bedrock type) would be more important than fire history in explaining the observed patterns of post-fire resilience in early successional vegetation.

To test our hypothesis we focused on the collection of in-field data on vegetation structure and on plant community structure from scrub formations at locations with different bedrock type, distinct fire frequencies and different time distances from the last fire event (see section 2.2.5). The use of vegetation and community structure, including features such as vertical strata, species diversity and plant functional diversity, to assess post-fire resilience has been used before by Pausas and Lloret (2007). These authors showed that the richness of plant functional types tends to decrease with fire occurrence at both landscape and patch scales, and that the spatial distribution of functional types with mechanisms allowing post-fire regeneration reproduces the fire distribution patterns, whereas functional types lacking these regeneration mechanisms tend to avoid burnt areas.

Based on vegetation and community structure of heath and broom scrub formations, our study revealed that, at local scales, geological factors can override fire history in determining post-fire vegetation recovery. In fact, no significant effects of fire history traits (frequency, and time since last fire) on vegetation recovery were found, whereas significant effects of bedrock type were recorded in most attributes of vegetation and plant communities assessed as response variables in our study, from species richness and plant functional groups to vertical and horizontal structure of vegetation (see section 3.4.2). Scrub formations on granitic soils tend to host more species and to exhibit more vigorous development than those on schistose soils, consistent with previous reports on the influence on bedrock and soil properties on vegetation cover in the region (Honrado, 2003; Honrado and Vieira, 2009). Ordination analyses (DCA; see Figure 3.19) highlighted that differences in species composition across all the plots were also mainly related to bedrock type, with a minor effect of fire history only found on granites.

Moreover, the prevailing effect of lithology over most of the tested plant functional classifications (see Figure 3.18) further highlighted its role as a driver of local patterns of post-fire regeneration. In our test region, vegetation plots on granitic soils usually hosted higher numbers of animal-dispersed woody species, of trees and tall shrubs, of woody deciduous species, and of forest, edge and tall scrub woody species. These functional groups are characteristic of later successional stages (Porto *et al.*, 2011) and are thus favoured by conditions enabling a rapid and vigorous development of woody vegetation, which seem to be provided by well drained deep granitic soils (Honrado, 2003).

Conversely, few significant effects of fire history were found for the tested functional classifications (see Figures 3.16 and 3.17). Seeder plants were the most striking exception, since they were represented by more species in locations that suffered a recent fire or that were submitted to multiple fire events in the focal time period. This is consistent with the fact that, in the Mediterranean, seeders are characteristic of early successional stages and frequently disturbed environments (Verdu, 2000; Porto, 2012).

Even if the effects of other factors could not be assessed due to the absence of adequate data (e.g. historical land use, microclimatic conditions), this set of results seem to demonstrate a key role of bedrock type (and related soil properties) as a driver of post-fire vegetation recovery in our test region. The several differences recorded in the structural development of post-fire scrub vegetation and in the functional profile of plant communities highlight the need to consider bedrock type (as well as other local environmental factors or gradients) when planning for the restoration of burnt areas (see below).

4.3. Implications for planning and management

The results from the several studies presented in this thesis have evident implications for several issues related to governance in the context of fire prevention and fighting as well as for the management of post-fire resilience in the context of ecological restoration, two important components of fire risk management (Chuvieco *et al.*, 2010; Hanewinkel *et al.*, 2010).

4.3.1. Fire risk management at national and regional levels

The results from the two studies analysing patterns of wildfire occurrence at regional and sub-regional scales highlighted the variability of fire regimes and of fire factors in heterogeneous countries or regions. In fact, we demonstrated that: (1) fire regimes are distinct across heterogeneous countries and so is the relative importance of fire factors, therefore fire regimes should be analysed on a regional basis; and (2) fire occurrence in environmentally heterogeneous (sub-)regions is explained by multiple factors, the ranking of which is region-specific, reflecting the distinct features and dynamics of social-ecological systems along environmental gradients within those regions.

Our results therefore suggest that, when planning for efficient wildfire prevention and allocation of firefighting resources at the national level, risk management authorities should consider the specificity of the several regions in terms of their environmental, socioeconomic and landscape attributes and dynamics. Moreover, our results highlight that this recommendation is also valid for planning at the (sub-)regional level, since many regions still hold high levels of heterogeneity that reflect downstream on the spatiotemporal patterns of ecological processes such as disturbances (Wu, 2013).

The distinct importance of landscape and socioeconomic factors in explaining wildfire patterns across regions in Portugal also has implications for preventive management of the several fire risk factors. In fact, landscape features were found to be most important as fire factors in the northern, more heavily burnt and heterogeneous regions, in which the patterns of the analysed set of socioeconomic factors were of negligible importance. Conversely, towards south topography and socio-economy overrode landscape features as the most important fire factors. Overall, this means that even minor land use changes (e.g. farmland abandonment or intensification in small-scale property and ownership landscapes) may have quite strong consequences for future wildfire regimes in northern regions, as described for other Mediterranean areas by Moreira and Russo (2007) or Silva *et al.* (2011), whereas in southern areas only a massive, unlikely change in land use patterns (e.g. abandonment or conversion of large, continuous areas of ‘montado’ into intensively managed forest stands) would eventually lead to shifts in fire regimes.

Climate was consistently found to be of low importance in our national, regional and sub-regional assessments of wildfire patterns and fire factors. However, climate data are widely used in the modelling of fire ignition as well as of fire behaviour (Westerling *et al.*, 2003; Aldersley *et al.*, 2011). In Portugal, fire occurrence is known to have a strong connection to weather conditions favouring ignition and spread over the landscape (Pereira *et al.*, 2005; Trigo *et al.*, 2006). However, there seems to be no significant connection between fire history and the main multiannual climatic patterns and gradients across the country, even if climate and weather conditions, particularly in extreme years, are recognised as important factors of wildfire occurrence (Pereira *et al.*, 2005).

Overall, our results confirm that detailed records of fire history and robust modelling frameworks are important assets to understand and predict fire patterns, at least at a decadal resolution. Those records as well as the spatiotemporal patterns there in should thus be more often considered in fire risk modelling. The continuous collection of information of fire occurrence, intensity and severity, and an investment in the improvement of predictive modelling frameworks, should thus be priorities for administration agencies dealing with spatial planning, rural development and natural resource management, fire risk management, and multi-scale governance (Chuvieco *et al.*, 2010; Thompson *et al.*, 2011; Mickler *et al.*, 2013).

4.3.2. Regional to local wildfire risk management and post-fire restoration

Fire risk management at regional to local scales (in Portugal, respectively districts and municipalities) should encompass several tasks, from the production of detailed fire risk maps at the pertinent scales and with an adequate frequency, to the planning and allocation of firefighting resources, but also landscape management for reduced probability of fire ignition and propagation (Moreira *et al.*, 2011). In this regard, the results presented in this thesis suggest that, when planning for efficient wildfire prevention and fighting at regional to local scales, among other factors attention should be paid to: (1) the relative importance of fire risk factors (or correlates) in each focal region, as revealed by analyses of recorded fire history; (2) the characteristic functional features of ecosystems and landscapes, particularly regarding their productivity and phenology; (3) the functional dynamics of vegetation, which promotes the accumulation of fuel biomass and thereby the proneness of landscapes to the occurrence of fires; and (4) regional and local factors determining vegetation development and phenology as well as post-fire regeneration.

Our study addressing post-fire resilience at the regional scale clearly demonstrated the relevance of functional approaches to analyse key ecosystem properties (Alcaraz *et al.*, 2006). Pre-fire conditions as well as the magnitude of the functional breaks induced by fire events were found to influence post-fire recovery rates. The post-fire recovery capacity is a key determinant of fuel biomass accumulation across the landscape (Lloret *et al.*, 2003; Moreira *et al.*, 2011), but it is also important to ensure rapid reestablishment of pre-fire ecosystem functioning and thereby the provision of valuable ecosystem services (Bugalho *et al.*, 2011; Duguy *et al.*, 2012). Therefore, at the regional scale, forest and landscape planning for improved post-fire regeneration should consider the functional dimension of ecosystems and landscapes besides their structural attributes, e.g. by using ecosystem functional types (Alcaraz *et al.*, 2006) to define broad planning and management units. This dimension adds to the several other applications of remote sensing tools in fire detection and in fire risk management (Chuvieco *et al.*, 2010).

From our study of post-fire resilience at the local scale we have concluded that geology plays a major role in determining the rates and pathways of vegetation recovery after fire. Together with results from the (sub-)regional analysis of fire patterns in the Alto Minho (see sections 3.2 and 4.1.1), this geological control over local post-fire recovery suggests that planning for improved post-fire resilience should consider geology in both regional planning and definition of local post-fire management priorities. In fact, the distinct rates of post-fire recovery as well as the different functional profiles of the resulting plant communities will have consequences for the provision of several regulating ecosystem services such as fire prevention, soil erosion control and water regulation (Smith *et al.*, 2011). Our results would thus also recommend that geology (among other local factors) should be considered when taking technical decision on post-fire restoration actions, particularly when establishing priorities for active restoration under scenarios of limited resources and in geologically heterogeneous areas. On substrates that are unfavourable for rapid vegetation recovery after fire (like schist soils in our test region), post-fire management of burnt areas may have to include active protection of soil against erosion as well as active plantation or seeding (e.g. Moreira *et al.*, 2012). Conversely, on favourable soils (e.g. those derived from granite in our test region), the rapid post-fire regeneration of dense scrub vegetation (and eventually woodland) would favour passive management as a possible strategy, e.g. by promoting supervised natural succession (Maguire and Menges, 2011; Camac *et al.*, 2013). Overall, this would allow an improved allocation of limited resources according to local needs.

Our results also suggest that geological factors should be considered in fire risk modelling, since differential resilience will lead to spatial variations in the accumulation and connectivity of fuel biomass across the landscape (Lloret *et al.*, 2003; Moreira *et al.*, 2011), resulting from the distinct post-fire development and functional profile (and possibly fire-proneness) of vegetation on soils derived from different bedrock types.

4.4. Synthesis and conclusions

In a nutshell, from our studies of the patterns of wildfire occurrence and post-fire resilience at several spatial scales in Portugal, we have concluded that:

- **On the patterns and drivers of wildfire occurrence:**

(1) Distinct factors drive wildfire occurrence across heterogeneous countries and regions, and this should be taken into consideration when planning for improved fire risk management across the several levels of political and technical decision;
(2) The ranking of fire factors or correlates, determined by environmental and social-ecological features of regions, can be revealed by analyses of historical fire records against multiple sets of explanatory variables, and is likely to be region-specific in heterogeneous countries;
(3) The diversity of fire factors required to adequately explain and predict fire regimes is higher in heavily burnt regions than in regions recording lower number of fires and lower values of burnt area; and
(4) Machine learning modelling techniques are useful to explain and predict the patterns and drivers of fire occurrence in heterogeneous countries and regions.

- **On the patterns and drivers of post-fire recovery:**

(5) Using functional indicators of post-fire recovery allows capturing dimensions of resilience that are driven by distinct sets of factors;
(6) Regional patterns of post-fire recovery rates are largely determined by size and other features of fire events, as well as by structural and functional attributes of pre-fire landscapes; and
(7) Geology is an important factor or correlate of both fire patterns and post-fire ecosystem resilience, and this should be taken into consideration in the spatial planning of forest resources and rural landscapes and in fire risk management at the regional and sub-regional levels.

- **On the implications for risk management and governance:**

(8) Regional to local rates and pathways of post-fire vegetation resilience are influenced by many distinct factors related to environmental conditions as well as to structural and functional features of landscapes and plant communities, which

should be taken into account for technical decision on active restoration of burnt areas;

(9) Fire recurrence and differential post-fire regeneration across burnt landscapes originates complex patterns of fuel biomass accumulation and connectivity, and this will influence the occurrence and spread of wildfires over the landscape; and

(10) Robust predictive modelling frameworks, coupled with historical fire datasets and remote sensing tools, can be important assets in the management of fire risk at several scales as well as in the monitoring of the effects of wildfires and other pressures on the key structural and functional attributes of landscapes and the ecosystems therein.

The research developed for this thesis has provided relevant results and conclusions, but it has also suggested that some questions will require continued investigation. First, from a methodological perspective, future research should aim to improve the several modelling frameworks used in the four studies and to test their predictive power across a wide range of conditions. Another promising line of research would focus on the application of remote sensing methods, particularly those based on free or low-cost satellite imagery, to predict patterns of wildfire occurrence and post-fire resilience at several scales and with the appropriate spatial and temporal resolutions, in connection with in-field campaigns for calibration and validation. Future research should also assess the individual and joint effects of other controls of local resilience, e.g. pre-fire community structure, landscape context and topographic attributes, in order to build a more integrative and informative predictive model of vegetation resilience. Finally, continued effort should be made to promote the application of results and lessons learnt in the improvement of fire risk management and governance across spatial scales and levels of political and technical decision.

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6. Appendices

Appendix 1

Reclassification of CLC categories into eight broad land cover categories.

523 code	**Sea and ocean**	
111	Continuous urban fabric	Urban/Artificial
112	Discontinuous urban fabric	
121	Industrial or commercial units	
122	Road and rail networks and associated land	
123	Port areas	
124	Airports	
131	Mineral extraction sites	
132	Dump sites	
133	Construction sites	
141	Green urban areas	
142	Sport and leisure facilities	
211	Non-irrigated arable land	Agricultural and agroforestry areas
212	Permanently irrigated land	
213	Rice fields	
221	Vineyards	
222	Fruit trees and berry plantations	
223	Olive groves	
231	Pastures	
241	Annual crops associated with permanent crops	
242	Complex cultivation patterns	
243	Land principally occupied by agriculture, with significant areas of natural vegetation	
244	Agro-forestry areas	
311	Broad-leaved forest	Broad-leaved forest
312	Coniferous forest	Coniferous forest
313	Mixed forest	Mixed forest
321	Natural grasslands	Scrub and/or herbaceous vegetation associations
322	Moors and heathland	
323	Sclerophyllous vegetation	
324	Transitional woodland-shrub	
331	Beaches, dunes, sands	Open spaces with little or no vegetation
332	Bare rocks	
333	Sparsely vegetated areas	
334	Burnt areas	
335	Glaciers and perpetual snow	
411	Inland marshes	Wetlands/water bodies
412	Peat bogs	
421	Salt marshes	
422	Salines	
423	Intertidal flats	
511	Water courses	
512	Water bodies	
521	Coastal lagoons	
522	Estuaries	

Appendix 2

Field recording form used in the each of the 40 locations.

Point nº	
military map 1:25 N^o:----------------------- --	I.F.N^o ------ Date/-----/----/08
UTM:-------- Lat.-------- Long. ---------	Photos:--------------------------------------
Alt.(m): ---- Area: 25m^2 Aspect: ---- Slope: …..%	Name:--------------------------------------
General notes :	Vegetation type: ------------------------------
	Phytosocioloy: Class: -----------------------------------
	Order: ---------------------------------
	Aliance: ---------------------------------
	Association: ----------------------------
	Percentage cover (strata) E1 ____ % E2 _____% E3 _____%
	Soil type:
	Geological form:
	Lithology :

N	species name	abundance
01.		
02.		
03.		
04.		
05.		

Appendix 3

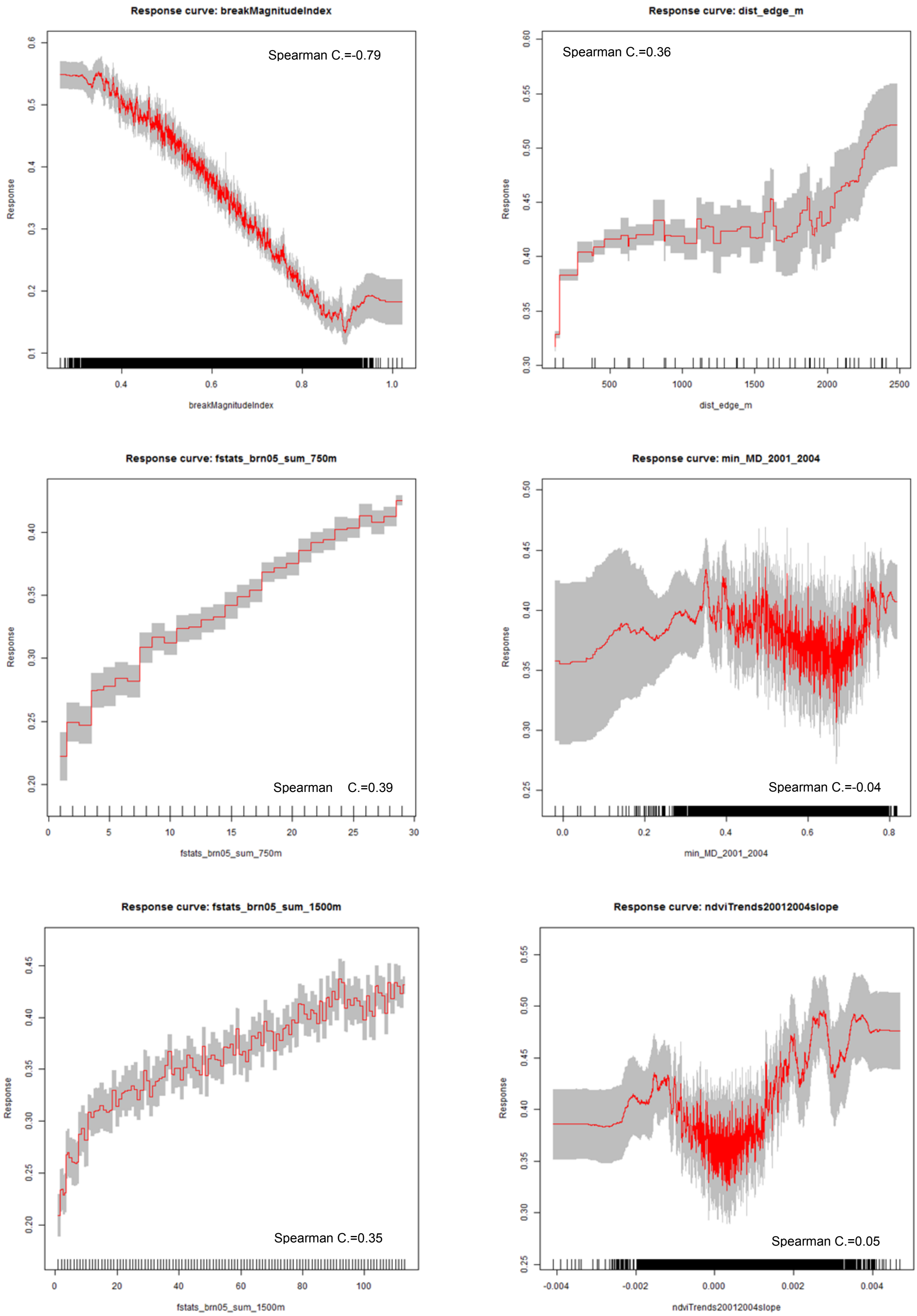

Figure a: Response curves for the 6 highest ranked explanatory variables in models for the Recovery Index indicator.

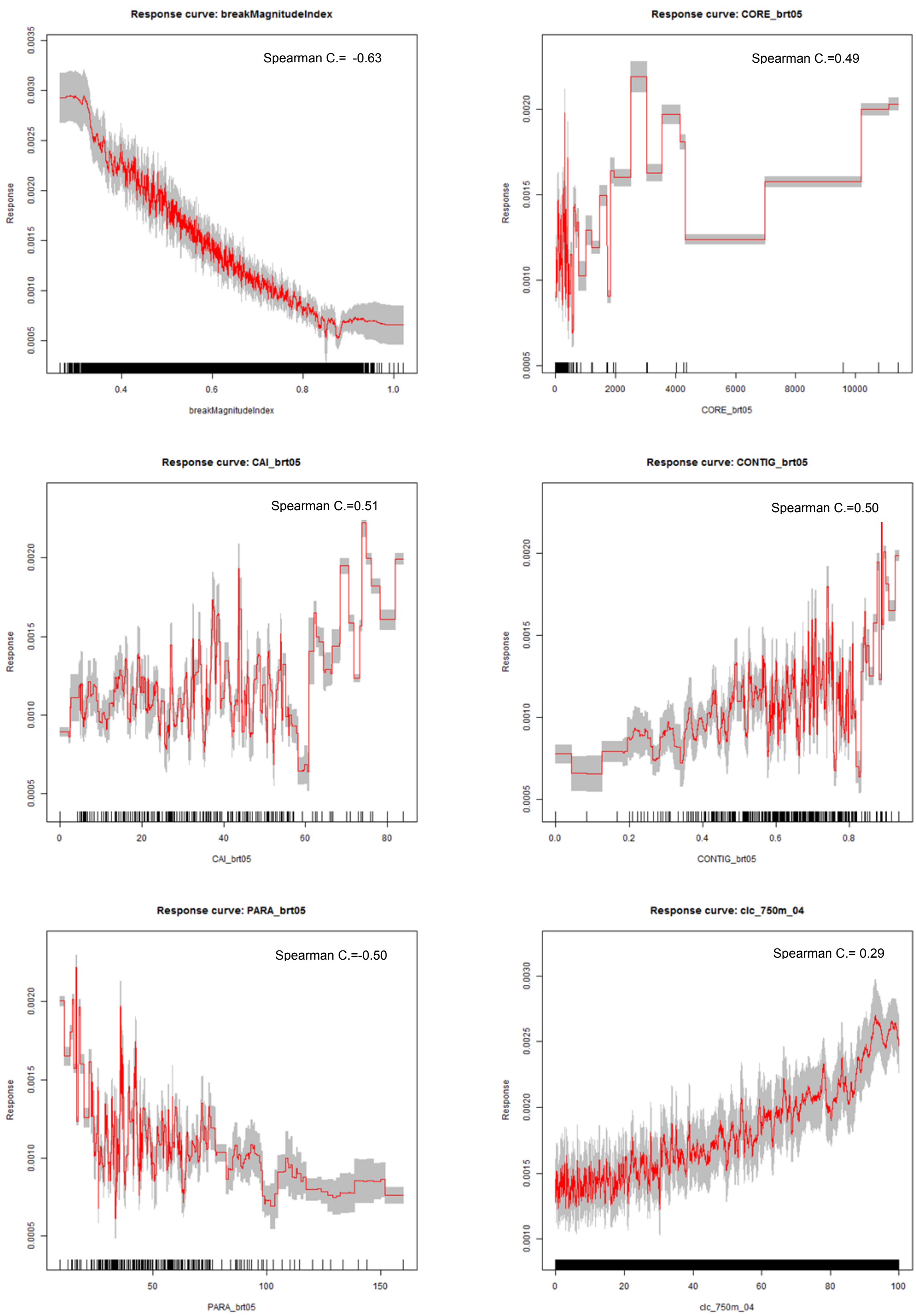

Figure b: Response curves for the 6 highest ranked explanatory variables in models for the Recovery Trend indicator.

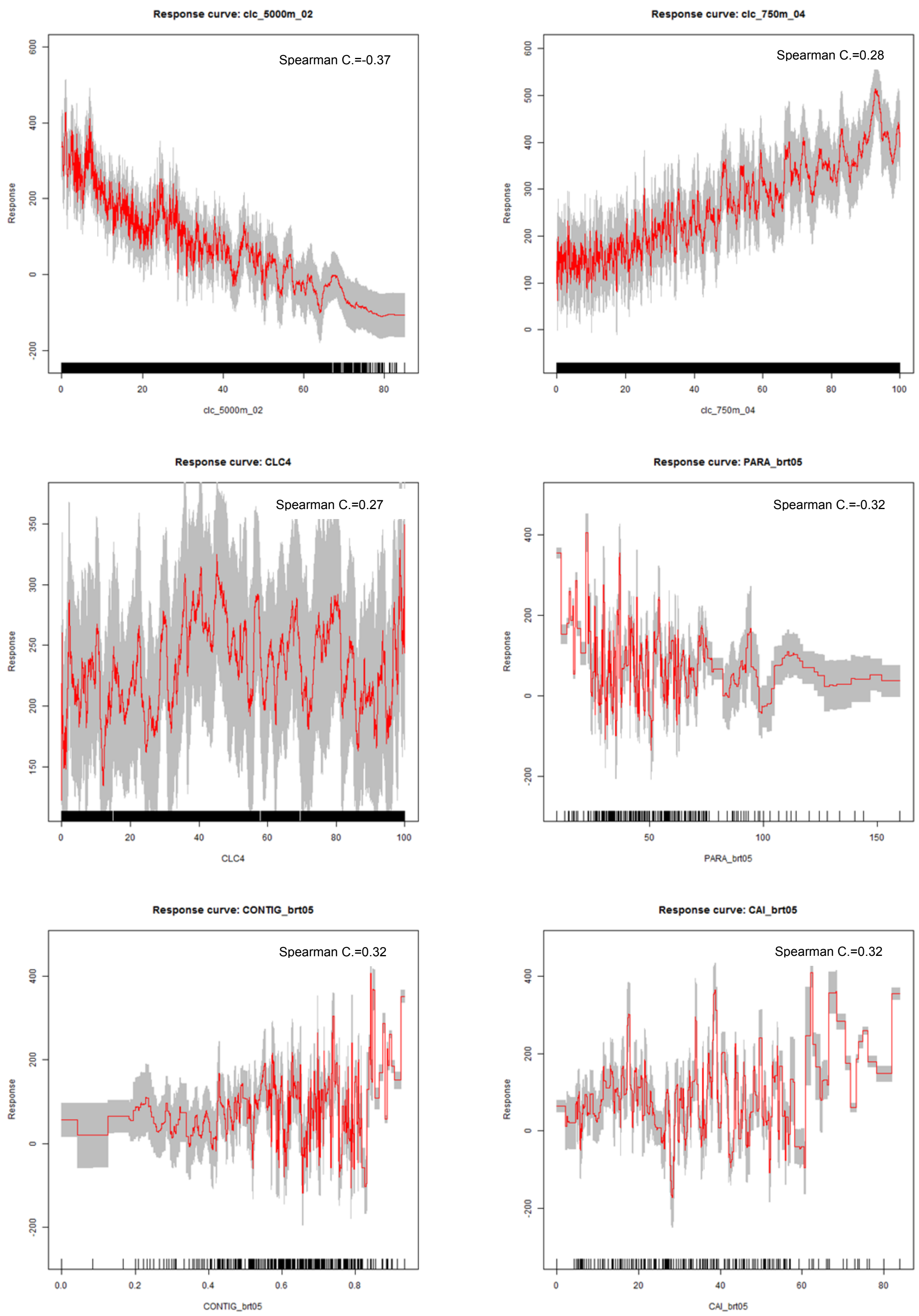

Figure c: Response curves for the 6 highest ranked explanatory variables in models for the 50% Recovery Time indicator.